STUDY ON STRATEGIC ISSUES PERTAINING TO THE APPLICATION OF BIG DATA ANALYTICS IN MANUFACTURING SECTOR SUPPLY CHAIN

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CANDIDATE'S DECLARATION

I, Narender Kumar, hereby certify that the thesis titled **"Study on strategic issues pertaining to the application of big data analytics in manufacturing sector supply chain",** submitted in fulfilment of the requirements for the award of degree of Doctor of Philosophy is an authentic record of my research work carried out under the guidance of Dr. Girish Kumar and Dr. Rajesh Kumar Singh. Any material borrowed or referred in the study is duly acknowledged.

The matter presented in this thesis has not been submitted in part or fully to any other University or institute for the award of any degree.

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CERTIFICATE

This is to certify that the thesis entitled **"Study on strategic issues pertaining to the application of big data analytics in manufacturing sector supply chain",** being submitted by Mr. Narender Kumar (Roll No.2K16/PhD/ME/41) to the Delhi Technological University Delhi for the award of the degree of Doctor of Philosophy, is a record of bonafide research work carried by him. He has worked under our guidance and supervision and fulfilled the requirement for the submission of the thesis, which has attained the standard required for PhD. Degree of Delhi Technological University, Delhi. The results presented in this thesis have not been submitted elsewhere for the award of any degree or diploma at any other university or institute.

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ABSTRACT

In the era of Industrial 4.0 all organization are moving towards digitalization of their processes. Due to the digitalization of processes, massive unstructured data is being generated in an organization from different sources. This huge amount of data is very difficult to manage with traditional decision-making tools. Therefore, Big Data Analytics (BDA) play an important role to manage/analyze such kind of data. There is lack of comprehensive and exhaustive study on implementation of BDA in manufacturing sector. In the context of the Indian manufacturing sector supply chain, the current study intends to investigate the barriers and critical success factors of BDA adoption. Many gaps need to be filled by conducting research, which gives a framework for the BDA application in the manufacturing sector.

Therefore, four objectives of this research have been developed based on the research gaps identified in the literature review. The first objective is to identify and justify the benefits of Big Data Analytics applications in the context of the Indian Manufacturing Industry. The second objective is to identify and analyze the key barriers obstructing the implementation of Big Data Analytics and develop framework for evaluating the barriers intensity index. The third objective is to Identify and ranking of Critical Success Factors in Big Data Analytics implementation. The fourth objective is to explore the determinants and develop a conceptual framework for adopting Big Data Analytics in the context of Indian Manufacturing.

Literature has been reviewed in the areas such as big data analytics (definitions, characteristics, application of BDA in manufacturing, identification of barriers, critical success factors, determinants, and items. The flow of this research goes as follows.

Initially, there is a need to justify the Big Data enabled manufacturing over without Big Data enabled manufacturing which has been done in the study using Analytical Hierarchy Process. In the study, it was justified that Big Data enabled manufacturing is better as compared to without Big Data enabled manufacturing. Then, identification and analysis were carried out for

the major barriers obstructing the implementation of Big Data Analytics and framework for evaluating the barriers intensity index in the context of the Indian manufacturing industry were developed. A total 17 barriers were identified through an extensive literature review and based on the opinion of experts from industry and academia. Factor analysis is applied to factorize the seventeen identified BDA barriers into three categories viz: organizational, data management, and human barriers. Further, Graph Theory Matrix Approach (GTMA) was employed to evaluate the barriers intensity index. In the results, the organizational barrier came out to be the most important barrier in the implementation of BDA. This study is further extended by Identifying and ranking of Critical Success Factors (CSFs) in Big Data Analytics implementation. Critical Success factors for BDA application in the manufacturing sector are identified through literature. After discussion with experts, 15 factors are finalized for their ranking from a strategic perspective. A questionnaire-based survey was conducted in the context of big data analytics applications in the Indian manufacturing sector. The experts were selected from industry and academia. The experts from industries and academia were requested to respond to the questionnaire designed for this study. The CSFs have been ranked by Fuzzy TOPSIS approach. Commitment and engagement of top management, strategy development for BDA, and development of capability for handling big data are prioritized as 1st, 2nd, and 3rd in their relative importance, which is crucial for BDA implementation. In addition to this, the Decision-Making Trial and Evaluation Laboratory (DEMATEL) approach categorizes the critical Success factors into cause-and-effect groups. Based on DEMATEL results, eight critical success factors are falling in the category of cause group and seven critical success factors fall in the effect group.

Finally, while exploring the determinants a conceptual framework for adopting Big Data Analytics in the context of Indian Manufacturing was developed. A structural modelling was used to examine the hypothesized conceptual research model using smart partial least squares

(PLS). All the path coefficients are positive, and the P value is in the acceptance range (P<0.005); hence the results support the hypothesis. The research work comprises the fulfilment of all objectives identified based on the research gaps. The achievement of the objectives of this research can assist managers or the top management in implementing new technologies. This thesis makes a novel theoretical and practical contribution. The significant contributions and research implications can be retrieved from the research. Recommendations, limitations, and future scope of the study have also been made. This research will help manufacturing organizations, academicians, and researchers to understand, adopt, and implement the learning based on the outcomes of the study.

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LIST OF ABBREVIATIONS

AHP : Analytic Hierarchy Process

ANP : Analytic Network Process

AVE : Average variance extracted

BA : Business Analytics

BDA : Big Data Analytics

BDM : Big Data-Enabled Manufacturing

CFA : Confirmatory Factor Analysis

CR : Consistency Ratio

DMATEL : Decision-Making Trial and Evaluation Laboratory

DMB : Data management Barriers

DOI : Innovation Diffusion Theory

EDI : Electronic Data Interchange

EFA : Exploratory Factor Analysis

ERPS : Enterprise Resource Planning Systems

FNIS : Fuzzy Negative Ideal Solution

FPIS : Fuzzy Positive Ideal Solution

GDI : Global Desirability Index

GPS : Global Positioning System

GTMA : Graph Theory Matrix Approach

HB : Human Barriers

I4.0 : Industry 4.0

IF-DEMATEL: Intuitionistic Fuzzy Decision-Making Trial and Evaluation Laboratory

IoT : Internet of Things

KMO : Kaiser-Meyer-Olkin

MCDM : Multi-Criteria Decision Making

OB : Organization Barriers

PCA : Principal Component Analysis

PLS : Partial Least Squares

PV : Priority Vector

RFID : Radio Frequency Identification

SAW : Simple Additive Weighting

SCA : Supply Chain Analytics

SCM : Supply Chain Management

SEM : Structural Equation Modelling

SMOs : Sustainable Manufacturing Operations

SPSS : Statistical Package for the Social Sciences

TFN : Triangular Fuzzy Numbers

TOE : Technology-Organization-Environment Framework

TOPSIS : Technique for Order of Preference by Similarity to Ideal Solution

WBDM : Without Big Data-Enabled Manufacturing

LIST OF SYMBOLS

B_i	: Absolute Value
Z	: Average Matrix
λ_{max}	: Average of the Elements of Matrix
$c*_{j*}$	: Benefit Criteria
C	: Closeness the Ideal Solution
d_j^-	: Cost Criteria Respectively
D^+	: Distance between to Fuzzy Numbers
D^-	: Distance of Rating
X_{ij}	: Elements of Average Matrix
n_{ij}	: Elements of Normalized Initial Direct-Relation Matrix
A^-	: Fuzzy Negative Ideal Solution
A^+	: Fuzzy Positive Ideal Solution
I	: Identity Matrix
V^-	: Negative Ideal solution
N	: Normalized Initial Direct-Relation Matrix
P_1	: Pairwise Comparison Matrix
P_2	: Principal Matrix
r_{ij}	: Relative Values
Y	: Total Relation Matrix
Yij	: Triangular Fuzzy Number for the linguistic Term
V*	: Value Considered for the Ideal Solution
W	: Weight of Criteria

CHAPTER 1
INTRODUCTION

The structure of this chapter is as follows: “Background” section deals with the research background of this study. In “Historical development of Big Data” section, the historical development of big data is discussed. “Concept of Big Data” section presents the basic concepts of big data. “Research Significance” section discusses the significance of the current research work. “Organization of thesis” section provides the outline of thesis. Finally, the summary of this chapter is provided in “Chapter Summary” section.

1.1 Background

Automation is becoming increasingly commonplace among manufacturers as the sector adapts to the digital age. Emerging technologies are becoming increasingly prevalent in the industrial sector. Businesses today use cutting-edge technology like big data analytics, AI, cloud computing, and the Internet of Things to boost productivity and reduce overhead. As manufacturing processes become increasingly digitized, huge amounts of unstructured data (big data) are produced. The Oxford English Dictionary defines “big data” as “a large data set that can be computationally examined to reveal patterns, trends, and interactions, especially those relating to human behaviour and interactions”.

However, this definition does not fully encompass the idea of big data., as big data must be differentiated from difficult-to-manage data using traditional data analysis techniques. (Arunachalam et al., 2018). As a result of the exponential increase in complexity, it requires advanced techniques for handling. Big data is a large dataset generated by organizations using intelligent devices that can only be stored, examined, and analyzed with advanced tools. Technological advancement is expected to predict the use of big data in manufacturing firms. Data is gathered from various sources like smart electronics gadgets, sensors, Radio-frequency identification (RFID), and other devices in manufacturing firms. It helps in the automation of manufacturing operations. Any manufacturing industry's profitability depends on increasing product quality and a higher production rate. Organizations are applying various measures of manufacturing performance to enhance profitability. In the manufacturing sector, big data analytics can help in trend forecasting, supply chain management, scheduling, etc. Therefore, investment in advanced technology to support strategic decision-making has become a crucial asset for firms to enhance performance (Wang et al., 2019). It refers to vast datasets with a wide variety and velocity of data, difficult to handle using traditional tools and techniques (Constantiou, and Kallinikos, 2015). Manufacturing uses big data analytics to increase productivity, automate operational processes, improve quality, and lower maintenance costs.

Big data analytics (BDA) analyzes extensive data with advanced technology to reveal important information (e.g., hidden patterns, unknown connections) that may be used to improve business operations within organizations. Analyzing large datasets reveals hidden patterns and correlations, trends, and other valuable information. That leads to improve the operational efficiency and exploration of new markets and opportunities (LaValle et al., 2011). BDA is generally related to data analysis and mining techniques used on a massive amount of data. Data is typically collected from various sources and processed through a sequence of procedures for meaningful analysis (Chen et al., 2014). BDA can be used in the multiple functions of supply chain operations, including sourcing, production, distribution, and marketing (Sanders 2016). Organizations that use developing technologies like BDA and artificial intelligence to improve their decision-making abilities have better operational results (Dubey et al., 2021). Furthermore, BDA investments yield benefits in terms of financial performance. This research study revolves around the application and issues of BDA in the manufacturing sector.

This chapter begins with an overview of the study's purpose and context, then moves on to a brief explanation of the research area, and finally concludes with an overview of the thesis's structure. Highlights from this chapter are depicted in Figure 1.1, a chapter flow diagram. The current study focuses on big data analytics, which is either currently utilised or planning to be adopted in the manufacturing sector in the Indian Manufacturing industries. By cutting costs and waste while increasing efficiency, manufacturers are taking steps toward a more sustainable future (Jabbour et al., 2020; Roy and Roy, 2019). Recently, there has been an uptick in manufacturers who recognise the value of sustainability. Manufacturing activities and the natural environment have a link, which is considered in real-time decision-making (Kamble et al., 2020; Raut et al., 2019). Many manufacturing organizations believe sustainable manufacturing and consumption to be viable strategies. Using this technique, the organization can achieve its overall development goals, which include a reduction in resource usage and pollution. This encourages businesses to conserve for future generations by decreasing energy usage while reducing costs (Roy and Singh, 2017).

Figure 1.1 Chapter Flow Diagram

The current scenario is becoming increasingly unclear and precarious in the business. As a result, figuring out how to adapt and change has become a significant task for the organization to meet sustainability.

The manufacturing sector generates a significant amount of unstructured data because of the use of numerous digital machines, electronic devices, and sensors on shop floors and production lines (Zhong et al., 2015). Managing this massive unstructured data is becoming a daunting effort for industry specialists. According to Brinch et al. (2017), BDA can aid in the simplification of this massive data for decision-making and operational planning. According to Gong et al. (2018), BDA applications are becoming increasingly popular across many supply chain activities. BDA is an innovative solution for managing and integrating data to improve production efficiency (Bi and Cochran 2014). Furthermore, BDA can aid plant automation in the fourth industrial revolution age (Telukdarie et al., 2018; Tseng et al., 2019). The employment of advanced analytic techniques such as applied mathematical analysis, predictive analytics, data processing, and so on is referred to as BDA. These strategies provide a better understanding of the processes, which aids in making timely and correct decisions and enhancing manufacturing operations (Sanders 2016).

BDA is not just used in the context of performance management, but also in healthcare and public services (Elgendy and Elragal, 2014). Better performance management is the end result of BDA's increased reliance on data in decision making. The health industry generates a large amount of data as a result of its need to track and record many aspects of patient care, recordkeeping, and compliance with laws and regulations. BDA can help doctors schedule appointments, prescribe medications, and make better decisions in the clinic. By applying predictive analytics and machine learning to large amounts of data and providing instantaneous access, BDA helps the government with a variety of tasks, including reducing crime, increasing government openness, and bettering transportation. Furthermore, because of the large amount of data collected from sensors and satellite photos, the government can foresee natural disasters ahead of time and take swift action to reduce damages. If predictive analytic techniques are used to monitor and forecast worker performance, higher productivity targets may be achieved. According to Zhong et al. (2016), BDA is important in the efficient management of the healthcare industry and the digitization of records. The term "digitalization of records" refers to storing all available data in a text-searchable format that allows users to find specific information quickly.

BDA shortens the time it takes to handle structured and unstructured data (Barlow 2013). BDA impacts overall business performance since BDA-enabled organizational actions help to reduce costs, increase product quality, and enhance product delivery (Lin et al., 2018). It aids organizations in making better forecasts. As a result, firms see cost savings, better operations planning, lower inventory levels, and waste elimination, among other things, because of their operational process improvements. As a result, it increases the organization's overall performance, such as profitability, productivity, and efficiency (Gunasekaran et al., 2017). According to Wamba et al. (2017), BDA can improve supply chain agility, adaptation, and operational excellence. BDA improves a manufacturing firm’s competitive edge by improving the decision-making process, allowing it to make faster and better judgments, and enhancing the organization’s capability (Dubey et al., 2016). It encourages innovation by giving valuable data to improve manufacturing operations and providing a mechanism to manage environmental uncertainty, improving the organization’s overall performance.

The use of predictive analytics powered by big data increases the longevity of industrial production (Gandomi and Haider 2015). The predictive analytics solutions from BDA use data mining techniques like machine learning, artificial intelligence, and pattern repository systems to help extract meaningful insights from data regarding potential future events. Long-term viability in the supply chain is enhanced by the use of AI and ML since these technologies reveal hidden inefficiencies, streamline decision-making, and enhance the purchasing experience for customers. To better the supply chain's sustainability, big data predictive analysis helps to identify and prioritise the most pressing environmental and social challenges. Manufacturing organizations should use BDA for long-term manufacturing processes, according to Dubey et al. (2016). Continuous real-time monitoring and analysis of operational data aid in removing bottlenecks. BDA aids in the discovery of defects, the prediction of machine failure, the reduction of risks, the improvement of performance, and the reduction of downtime.

BDA may assist manufacturing firms in more effectively implementing sustainable practices to increase productivity. By better managing sustainability strategies of reducing, reusing, and recycling, big data may help support and improve sustainability measures in diverse activities. BDA also ensures lean and green production by maximizing resources (Gunasekaran et al., 2017; Ji-fan Ren et al., 2017; Doolun et al., 2018). Sustainable manufacturing practices boost company performance by conserving resources and reducing adverse environmental effects

(Braganza et al., 2017). Bag et al. (2020) found that big data analytics contributes to green product creation and sustainable supply chain results in the South African mining industry. The environmental impact of manufacturing processes can influence the organization's long-term reputation (Wood et al., 2016).

Manufacturing companies gain from cost savings, improved operations planning, lower inventory levels, better labor organization, and waste elimination because of BDA implementation and improvements in operations effectiveness and customer service. According to Popovic et al. (2019), implementing BDA saves material usage (10-15%), energy consumption (about 5%), scrap and rework (around 15%), and manual labor (about 20%). In addition, their research found that implementing BDA lowered maintenance and waste expenses by 12.5% on a year-over-year basis. On the other side, it improves consumer satisfaction, particularly regarding the delivery of items to the customer. Companies implement effective decision-making processes based on meaningful data derived from data analytics, allowing them to operate smarter, more flexible, and more efficient organizations (Demirkan and Delen, 2013).

1.2 Historical Development of Big Data

The term "big data" has been used since the early 1990s. It is not a new concept; people have been attempting to use data analysis methodologies for decision-making for a long time. However, during the last 20 years, data generation has changed rapidly and at a rate much beyond individual understanding (Donoho, 2015). Database management and data warehousing are the two most important aspects of the first phase (Lohr, 2014). It establishes the foundation for modern data analysis techniques such as fuzzy logic, database queries, evolutionary programming, and artificial neural networks. The Internet and the Web have brought new data collection and analysis opportunities since the early 2000s. The second phase of data started a new era of possibilities.

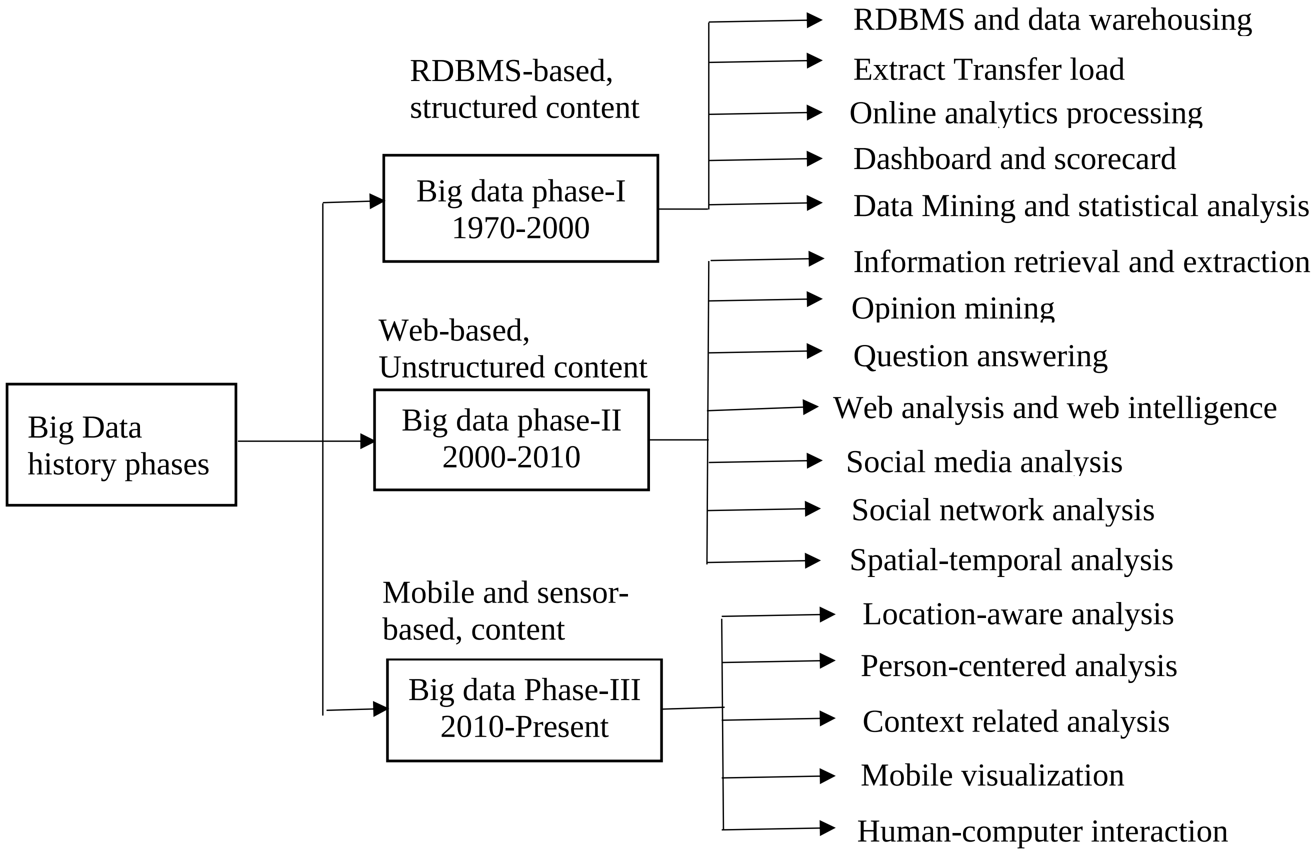

Figure 1.2 Phases of big data Evaluation; (Source: Big data framework 2019)

An enormous rise in semi-structured and unstructured data has been caused by HTTP-based web traffic. (Big data framework 2019). Companies must develop new techniques and storage options to evaluate this data type. It can be divided into the three phases to demonstrate the growth of big data evaluation (refer to Figure 1.2).

The growth of social media data has heightened the demand for analytics tools that can extract relevant information from unstructured data. Mobile devices are already giving new means to collect meaningful information, even though many organizations' primary focus on data analysis is still web-based unstructured content. In the third phase of big data, the rise of sensor-based internet-enabled gadgets is generating unprecedented amounts of data (Mukhopadhyay et al. 2021).

1.3 Concept of Big Data

Big data refers to datasets that have grown too large and complex to handle using traditional methods. Big data requires more advanced methods of addressing it due to its exponentially increasing complexity. (Arunachalam et al., 2018). Big Data are datasets that cannot be collected, stored, managed, and analyzed by conventional database software because these are massive datasets (Manyika et al., 2011).

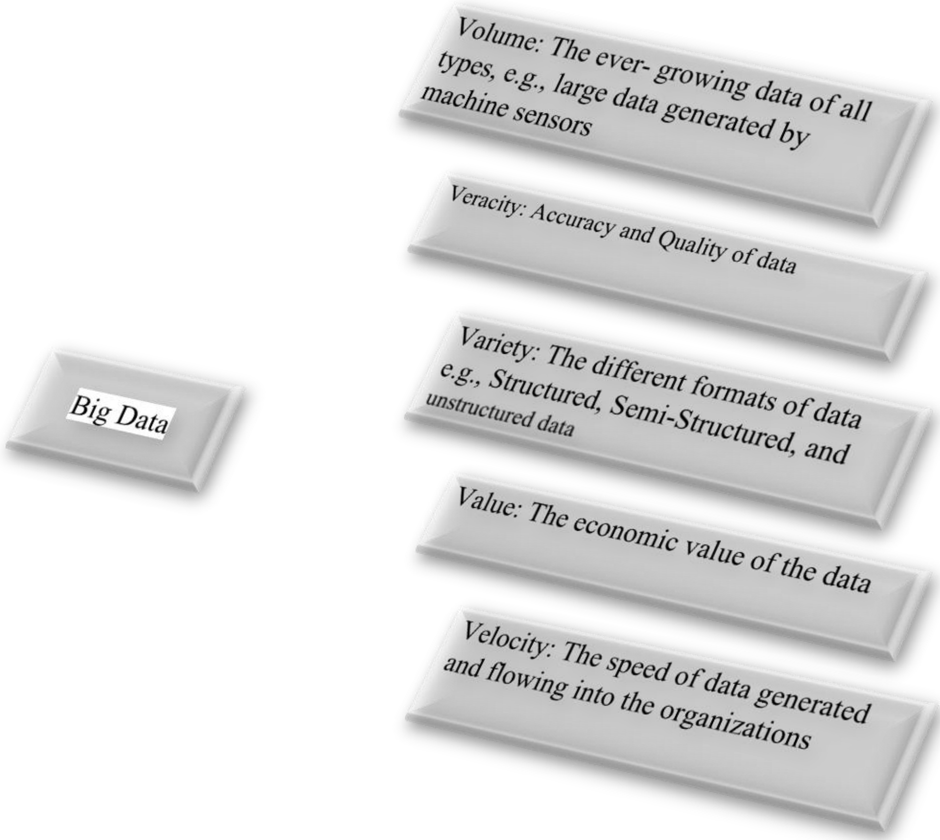

Figure:1.3 Big Data from the Aspect of 5 V's (Source: Self)

The 5Vs (refer to Figure 1.3) stand for volume (dimension of data), velocity (flow rate of data), variety (various forms of data), veracity (uncertainty of data), and value (quality of data) in the context of big data (AI-Barashdi and Karousi, 2019).

- *Volume* refers to the amount of data captured and stored in Giga Bytes, Tera Bytes, Peta Bytes, Exa Bytes, Zetta Bytes, and Yotta Bytes.
- *Variety* refers to unstructured, semi-structured, and structured data.

- *Veracity* refers to a data set's accuracy. It assists in determining what is important and what is not, as well as generating a deeper understanding of data so that action may be taken.
- *The value* determines how well data quality contrasts with the desired results.
- *Velocity* indicates the speed with which data is generated, collected, distributed, and real-time processing of streaming data

1.4 Research Significance

The present research work is expected to be useful for the manufacturing industry and sustainable manufacturing operations. The significance of the research is as follows.

- As a result of implementing big data analytics, businesses should see improvements in a number of areas: operational performance, responsiveness to supply chain challenges, inventory management efficiency, the ability to make strategic decisions, and the long-term viability of their manufacturing operations.
- Using BDA, manufacturer can boost production quality, expand their markets, and increase their openness to customers.
- Through BDA, partners in the industrial supply chain can gain visibility into all aspects of their operations, which in turn improves the quality of their decisions.
- By analysing past performance and making plans for the future, manufacturing companies can become more competitive on a worldwide scale.
- Manufacturers can learn the metrics used to assess their business, allowing them to focus on strengthening areas where they fall short and ultimately boosting customer satisfaction.
- The manufacturer can explore technological, organizational, and environmental characteristics influencing BDA adoption intentions in manufacturing operations.

1.5 Organization of Thesis

This thesis is organized into seven chapters as given below.

Chapter 1 deals with the introduction of this research, which focuses on the topic of the study. The background of the study explains why manufacturing organizations shift from traditional manufacturing processes to digital manufacturing methods. The thesis outline is presented at the end of this Chapter.

Chapter 2 comprises a literature review highlighting the concept of BDA in the manufacturing sector. This chapter also discusses the main BDA benefits, critical success factors, and barriers to BDA application for the manufacturing industry. Following the study's research objectives, the research gaps serve as the motivation for why this study is so important. This chapter concludes with the justification of research objectives by identifying literature gaps.

Chapter 3 presents the research methodology used for this study. The various multi-criteria decision-making approaches and detailed procedures of these approaches have also been discussed in this chapter.

Chapter 4 analyzes barriers to BDA implementation using factor analysis and Graph theory matrix analysis. Thus, based on the intensity index, find out the most critical barrier to implementing BDA in the Indian Manufacturing Industry.

Chapter 5 presents the modeling of critical success factors for BDA implementation. The justification provides various benefits of BDA and, thus, builds the foundations for further research on BDA in manufacturing. The various critical success factors are prioritized based on the ranking from the statistics.

Chapter 6 Deals with Hypotheses development and Testing and shows the empirical results and findings of the study. Data analysis was conducted using SPSS, ver.25, and Smart PLS.

Chapter 7 presents the conclusions drawn from the study and recommendations for future research. The most important critical success factors and barriers are observed. A summary of the findings for applying the big data analytics framework is discussed.

1.6 Summary of Chapter

This chapter established the context for the study and justified the investigation of BDA adoption in the Indian manufacturing sector. In this Chapter, the background of research has been discussed. The historical development and concept of big data analytics have been introduced in detail. The structure of the thesis and the brief description of all chapters have also been mentioned. Thus, this thesis makes a novel theoretical and practical contribution. In the next chapter, a literature review on various aspects of the study will be undertaken.

CHAPTER 2

LITERATURE REVIEW

A thorough literature review and the outlines the research's context are presented in this chapter. The structure of this chapter is as follows: “Introduction” section provides introduction of this study. In “Overview of BDA” section, the overview of big data is discussed. “BDA applications” section presents main applications of BDA. “Benefits of BDA” section benefits of BDA discussed. “Barriers for Investment in BDA” section provides the main barriers for BDA adoption. “Identification of Critical Success Factors to BDA Implementation in Manufacturing” section presents the key CSFs to BDA Implementation in Manufacturing. “Research Gaps” section deals with the research gaps for current study. “Research Objectives” section provides research objective for this research work. Finally, the summary of this chapter is provided in “Chapter Summary” section.

2.1 Introduction

A thorough literature review has been conducted to explore the prior research efforts and directions connected with the focus topic. The literature review aims to highlight research motivations and identify research gaps. The literature study begins by giving a general overview of BDA. Additional topics covered in the diverse literature include BDA applications for manufacturing operations, CSFs for BDA implementation in the manufacturing sector, and Barriers to Investment in BDA. Additionally, several specific critical success factors that serve as enablers for adopting BDA have been identified. Although there are many critical success factors, big data analytics deployment is not without its challenges. The implementation of BDA is hampered by several recognized barriers, which would prevent achieving Environmental, Social, and Economic Performance. Thorough literature research was conducted to identify critical barriers to adopt BDA in the manufacturing firms.

The literature review emphasized the need to study BDA, critical success factors, applications, and barriers in BDA investment. The following section will provide a thorough literature review of BDA in the manufacturing industry. Figure 2.1 illustrates the chapter's flow.

Figure 2.1 Chapter Flow Diagram

2.2 Overview of Big Data Analytics

There has been a massive growth in the quantity of data created by the number of transactions in manufacturing sector (Tiwari et al., 2018; Stefanovic, 2014; Chae et al., 2014). Approximately 2.5 billion gigabytes of data are being generated daily, and this number is predicted to expand to zettabytes in the coming years (Ganeshan and Sanders 2018). In supply chain operations, transaction-based data production is critical. Online retailer Amazon sells 600 goods each second, and Walmart processes more than one million transactions per hour, providing massive amounts of data for the company (Ganeshan and Sanders 2018). It is impossible to ignore the enormous amount of data referred as "big data" (Barton and Court, 2012); however, organizations continue to have difficulties in dealing with "big data" (Schoenherr and Speier-Pero, 2015; Tiwari et al., 2018). The first challenge is to define big data and how it is used in different sectors. The three V's of 'big data,' invented by Cox and Ellsworth in the late 1990s, are commonly described as Variety, Volume, and Velocity. Volume indicates the vast amounts of data that are accessible; Velocity belongs to the frequency with which data is generated or delivered; and Variety means data generated from various formats and sources (Russom, 2011). The researchers have since added two additional V's, including Value (the significance of getting economic gains from big data) and Veracity (the significance of the data quality and the trust level in several data sources) (White, 2012). Varied forms of data, such as texts, images, audio, and video, as well as different data formats, such as unstructured, semi-structured, and structured data, are now accessible because of technological advancements. According to a recent study, unstructured data accounts for more than 90% of big data (Ebenezer and Durga, 2015; Gandomi and Haider, 2015). Traditional statistical methods and tools cannot handle and analyze the rapidly changing, vast amounts of data from various sources to arrive at meaningful judgments because of the characteristics of big data (Kaisler et al., 2013; Wang et al., 2016a). BDA may be used to store, analyze, and manage huge amounts of data, particularly in the supply chain (Tiwari et al., 2018). BDA indeed combines two distinct technological disciplines. First, a tremendous amount of data can be mined for information. In the second place, various analytical tools can be used to analyze and understand this information (Russom, 2011).

In contrast to popular belief, big data is not a new phenomenon; but the capacity to use massive data via analysis and interpretation is a recent development (Arunachalam et al., 2018; Russom, 2011). BDA is part of a continuum that has been expanding and rising in complexity since 1950 to meet companies' requirements to process and analyze data as the type of accessible data has gotten more complicated (Refer to Figure 2.2). In the 1970s, advances in statistical approaches, in the 1980s data mining methods, in the 1990s, the notion of BI (Business Intelligence), termed BI 1.0 first-generation were developed (Chen et al., 2012). Tools, strategies, and processes for analyzing data to obtain meaningful information to enhance operational and tactical decision-making are referred to as business intelligence (Gudfinnsson et al., 2015). Data mart, data sources, data warehouse, and reporting and query tools are the four primary components of business intelligence (Sahay and Ranjan, 2008; Llave, 2017), the most essential of them is a data warehouse, which is a database that stores both internal and external data (Gudfinnsson et al., 2015). With the use of statistical approaches, data mining, and prediction, these aspects allow business intelligence to enhance decision-making (Sahay and Ranjan, 2008; Llave, 2017). During the early 2000s, the expansion of Internet technology allowed for the BI second generation, often called BI 2.0. Business analytics (BA) is a substitute for BI 2.0, described using data analytics methods in various industrial sectors (Chae et al., 2014). BDA's ability to store a large array of unstructured and structured data from various sources in real-time distinguishes it from typical business intelligence practices, whereas conventional BI tools may further only analyze structured data from homogeneous sources periodically (Vera-Baquero et al., 2015; Arunachalam et al., 2018).

The fundamental benefit of BDA tools is their technical capacity to efficiently use more modern databases, including NoSQL or Hadoop, to collect and handle enormous amounts of data from heterogeneous formats and sources using advanced analytical methods (Mortenson et al., 2015). There is collective agreement among academic experts and industry professionals that BDA has various benefits (Tiwari et al., 2018; Zhong et al., 2016). To have a strong knowledge of the potential advantages of BDA, companies have been progressively attempting to establish and strengthen their BDA capabilities (Tiwari et al., 2018).

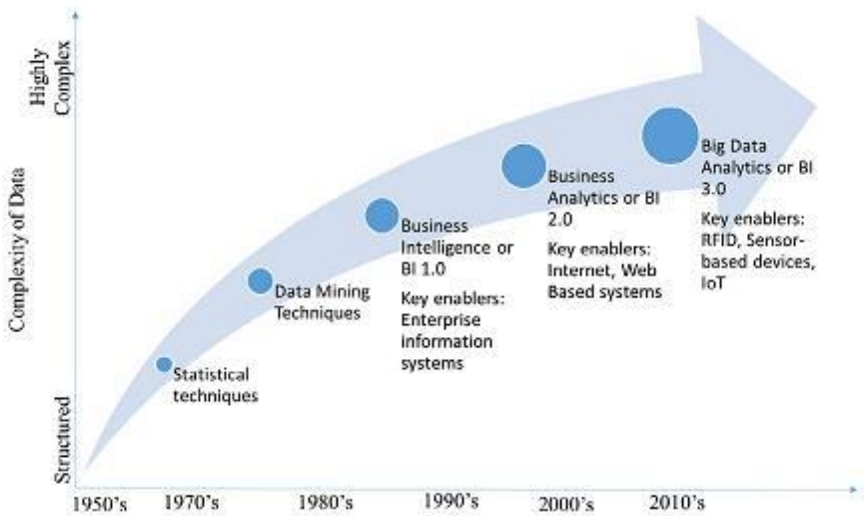

Figure 2.2 Big Data Analytics Development (Source: Arunachalam et al., 2018)

A thorough and comprehensive examination of big data may provide a wealth of data about consumer behavior, operational expenses, and market (Russom, 2011). Thus, businesses may better manage their customer relationships, explore new markets for their goods, enhance efficiency, and make better business choices, all leading to improved profitability (LaValle

2011). Big data has many uses in the public domain, including manufacturing, IT, healthcare, finance, supply chain, and logistics management (Zhong et al., 2016). BDA is used by consulting firms, including McKinsey & Company, to give business recommendations to its clients to enhance their performance, including the introduction of digital technology in banks based on consumer behavior analysis (Biesdorf et al., 2013). Big data is also used by retailers like Amazon for anticipatory logistics, which predicts what buyers will order before they buy a product. Intel, a technological corporation, also uses big data to speed up the expansion and introduction of new goods (Zhong, 2016). SCA has lately been a part of the business agenda due to its ability to cope effectively with corporate difficulties such as managing massive data and business risks (Manyika, 2011; LaValle et al., 2011). Some research, for example, looked at how BDA may help enhance organizational performance. With the moderating impact of analytics capability-business scheme orientation, Fosso et al. (2016) explored the relationship between BDA (covering three primary scopes such as technology, management, and talent capability) and the performance enhancement of an organization. Wamba (2017) performed a survey-based study in China and established a BDA capabilities model to examine how BDA affects an organization's effectiveness, guided by a resource-based perspective. Chae et al. (2014) investigates the impact of data accuracy and analytics on organizational performance, with supply chain management efforts serving as a moderating and mediating resource. Big Data is an extensive data set with various kinds that are challenging to analyze using typical data processing platforms or state-of-the-art data processing methodologies.

- Laney (2001) outlines the notion of Big Data is recognized by the 3V’s: "volume, velocity, and variety." Many more V’s have evolved in addition to these three core V’s. However, they vary depending on what specific characteristics the writers of these publications need to include.
- Big Data is high-variety, high-volume, and high-velocity data assets that need innovative forms of processing to allow better decision-making, process optimization, and insight

detection (Laney 2012). More broadly, data collection is considered Big Data if it is difficult to gather, curate, analyze, and visualize with existing technology.

- Big data is a cultural, technical, and intellectual phenomenon centered on mythology, technology, and analysis (Boyd and Crawford, 2012).
- Big data is characterized as high-velocity, high-variety information, and high-volume assets that need cost-effective, creative information formats for improved decision-making and understanding (Laney, 2012).
- Jeong and Ghani (2014) published a review of semantic techniques for Big Data, concluding that more effort should be put into proposing novel methods and that tools should be developed to assist practitioners and researchers in realizing the true power of semantic computing and solving critical big data concerns.
- Big data analytics has been highlighted as a vital technology to assist data collection, storage, and analyzing the data in contemporary manufacturing (Bi & Cochran 2014).
- Hazen et al. (2016) claimed that supply chain workers are overloaded with data, prompting new methods of thinking about data production, organization, and analysis. As a result, the amount, velocity, and variety of data encourage businesses to embrace and develop data analytic functions (i.e., big data, data science, & predictive analytics) to enhance operational performance.
- According to Sun et al. (2018), “big data” refers to data that is heterogeneous, autonomous, multidimensional, complex, dynamic, and developing, and that is beyond the ability of standard procedures or instruments to acquire, store, manage, analyze, and exploit.
- Gandomi and Haider (2015) listed many methods for improving decision-making skills, which were previously restricted in the conventional data period (such as audio, text, social media, predictive, and video).

The different stages in the manufacturing industry where big data analytics used are as follows:

- ***BDA in Plan Process:***

Incorporating analytics into the planning procedure may aid in predicting market demand for goods and services (Biswas and Sen, 2016). Demand forecasting is an important aspect of operations and supply chain management because it allows producers to approximate demand for their goods and limits the risk of uncertainty at the planning stage of their business (Lamba and Singh, 2017). This shows that BDA managers are more concerned about improving their demand prediction (Chase, 2013; Tiwari et al., 2018). The innovative techniques have made it possible for businesses to amass massive data on their clients' purchasing habits or sales that they may use to make accurate forecasts. Despite this, the great bulk of the data has not been put to good use or analyzed to its full potential. There was only a little amount of study on BDA forecasting before 2012, which led to the lack of research in this field (Lamba & Singh, 2017). According to research on retail businesses in Switzerland, BDA analytics increased the precision of predicting projections by a significant margin (Hofmann and Rutschmann 2018). It was shown that weather and real-time traffic data might predict electric car charging demand and assist designers in designing their infrastructure. To better manage airport operations and eliminate prediction mistakes, (Shin and Kim 2016) utilized search engine data to predict airline passenger demand. As a result, an effective inventory prediction may be a strong management and marketing tool to better handle inventories to satisfy consumer demands (Tiwari, 2018).

- ***BDA in Source Process:***

Finding new prospects in the sourcing process may be easier using BDA. By incorporating BDA into the purchasing process, suppliers will be evaluated and selected more effectively (Biswas and Sen, 2016). BDA's assistance enables enterprises to efficiently examine and monitor the efficiency of their suppliers in the context of sourcing (Wang et al., 2016b). There are several ways to collect and analyze information regarding the performance of supplier criteria, including delivery time and quality or pricing, to help organizations make better choices (Wang et al., 2016b; Tiwari et al., 2018). BDA may help in choosing suppliers who can provide raw materials at a cheaper cost or of greater quality and who can supply them more quickly and efficiently. To construct a useful model for sourcing suppliers across multiple sectors, BDA may be used to examine a wide range of variables (Lamba and Singh, 2017). Using analytics approaches like fuzzy synthetic assessment and analytic hierarchy process, Jin and Ji (2013) proposed a supplier selection model that decreases supplier selection risk and enhances the dependability of picking supply chain associates, contributing to higher effectiveness. Lamba and Singh (2017) claim that using BDA in this procedure may lower yearly source expenses between 2% and 5%. According to the authors, there is a significant amount of time spent obtaining and looking for information in enterprise resource planning systems (ERPS), which is a huge negative point. Big data, on the other hand, is efficient in acquiring and collecting data far more rapidly than traditional databases. For example, BDA may identify current trends or patterns in data, which may result in more dependable and accurate projections, making organizations more proactive instead of reactive in their sourcing approach (Lamba and Singh, 2017).

- ***BDA in Make Process:***

Using BDA throughout manufacturing might benefit companies by helping them plan production (Biswas and Sen, 2016). BDA is crucial in acquiring, storing, and analyzing data in manufacturing applications (Bi and Cochran, 2014). Manufacturing companies have often used methodologies like six sigma and lean thinking to reduce waste and delays in production (Auschitzky et al., 2014). Even though a considerable amount of data is generated throughout the production process, BDA has not yet been completely implemented (Weng and Weng, 2013). In the production process, BDA provides several practical benefits (Lamba and Singh, 2017). For example, big data has helped Merck reduce the waste rate and produce vaccines quicker, Xerox improves customer service while lowering costs, and Volvo foresees vehicle component failure. BDA has also been employed in smart systems to optimize energy output. Real-time data were studied to create a model for energy management systems in industrial contexts that minimizes emissions and production expenses (Katchasuwanmanee et al., 2016). By connecting external suppliers and consumers with production systems, BDA may also help inventory management (Tiwari et al., 2018). Sharma and Garg (2016) have investigated the role of BDA in enhancing the inventory process and making better purchasing choices.

- ***BDA in Deliver & Return Process:***

A fundamental part of actions and supply chain management is the movement of products through warehouses and managing activities connected with delivery/return, including transportation or material handling (Lamba and Singh, 2017). BDA will manage logistics to ensure that the appropriate items are delivered to consumers at the appropriate time (Biswas and Sen, 2016), while inventory management and supply chain procedures are improved in the return practice (Raman et al., 2018). Smart gadgets, mobile applications, RFID, GPS traffic information, weather forecasts, and EDI transactions are just some data sources created throughout the delivery and return operations (Lamba and Singh, 2017). BDA deployment in logistics and transportation has numerous advantages, including the efficient storage and processing of large data sets created by different sources, the development of smart logistics projects informed by gathered data, real-time traffic monitoring, and the development of anticipatory logistics, which may result in enhanced customer satisfaction and expanded sales (Ayed et al., 2015). Expenses associated with logistics operations depend significantly on human resources. In this area, BDA can assist in finding the best delivery routes, using human resources to keep expenses in check, and ensuring vehicle safety and proper maintenance (Wang et al., 2016a). In the logistics industry, the usage of BDA is still immature, and it is primarily employed for the goals, and fleet refueling, optimizing vehicle maintenance as well as delivery times, and forecasting accidents based on the performance of the drivers (Frehe et al., 2014; Hopkins and Hawking, 2018).

Organizational competitiveness and productivity are intricately linked to the efficiency and appropriateness of their logistics operations, with lower logistics costs resulting in higher profitability (Lamba and Singh, 2017). There are numerous instances of how BDA has been used in the delivery and process. To enhance corporate decision-making capability, a study was done in India to monitor the logistic fleet in real-time and collect data based on many parameters like speed, position, and fuel usage. Hundreds of automobiles were part of the initiative, which used wireless connectivity to send data to the organization's computer every two seconds. Hadoop, an analytics platform, was used to handle the vast data. This aided the company's efficiency and cost-cutting initiatives (Ayed et al., 2015). BDA has been applied in the marine shipping industry to address operational and strategic concerns across such a large network of carriers (Brouer et al., 2016). In metropolitan settings, BDA may be utilized to increase the distribution efficiency of manufacturing supplies by sharing transportation capacity (Mehmood and Graham, 2015). Investments in BDA made by third-party logistics services also improved the efficiency of BDA's operations, allowing for better visibility (Tiwari, 2018).

2.3 Big Data Analytics Applications

In the prevailing economic slowdown business environment, manufacturers aim to reduce waste and improve value. Customers seek high-quality, low-cost products (Dubey et al., 2016; Fercoq et al., 2016). Therefore, there is a challenge front manufacturing organizations to meet these expectations. BDA may be a possible solution to this problem due to its many benefits. This section provides the various BDA applications in the manufacturing sector from a sustainability perspective from the existing literature, which is summarized in Table 2.1. The main applications of BDA in manufacturing operations are enhanced production recovery/reuse, energy-efficient and safe processes, improved customer satisfaction, improvement in profit margin, waste minimization, resource optimization, and development of sustainable capabilities.

Table 2.1 Big Data Analytics Applications

Applications	Description	References	Sustainability Aspects		
			Economic	Social	Environmental
Enhanced production recovery and Reuse (EPRR)	Refers to an increase in the production rate of a manufacturing system that is achieved through the implementation of various techniques	Lee et al. (2015), ElMaraghy et al. (2017), Amui et al (2017)	√		√
Energy-efficient and safe processes (EESP)	Reduce the amount of energy required to provide products and services	Raut et al. (2019), Wang et al. (2019), Das et al. (2020)	√	√	√
Improved customer satisfaction (ICS)	Continuous change in expected performance by accurate forecast to meet organization targets	Dubey et al. (2016), Raut et al. (2019), Gawankar et al. (2020)		√	
Improvement in profit margin (IPM)	Refers to increase the amount of profit made from the sale	Gawankar et al. (2020),Wang et al. (2019)	√		

Waste minimization (WM)	A systematic method for the minimization of waste within a manufacturing system without sacrificing productivity, which can cause problems.	Song et al. (2019), Manavalan and Jayakrishna (2019), Cui et al. (2020)	√		√
Resources Optimization (RO)	Refers capacity to use intricate resources in an efficient way to accomplish a sustainable goal	Amui et al. (2017), Singh and El-Kassar (2019), Song et al. (2019)	√		√
Developing sustainable capabilities (DSC)	The ability of firms to respond to their short-term financial objectives as well as future goals	Singh and El-Kassar (2019), Amui et al. (2017)	√	√	√

These applications are further classified into three aspects, i.e., economic, social, and environmental. The application "Enhanced production recovery/ reuse" refers to an increase in the production rate of a manufacturing system that is achieved through the effective implementation of various techniques such as Lean, Kaizen, six sigma, cloud-based enterprise resources planning, etc., with the help of BDA. Reuse infers that the second user utilizes things without prior operations or as originally designed. The consumption of energy, impact on the environment, and cost, would be reduced by accurate and timely decisions taken with the support of data analytics (Hazen et al., 2016; Raut et al., 2019). "Improved customer satisfaction" is the continuous change due to optimal forecasts to meet organization targets and customer requirements. By utilizing BDA, the customer may be effectively involved with green purchasing practices (Raut et al., 2019). For instance, optimization and machine learning have been used to select suppliers with low carbon emissions. Supply chain carbon maps are generated using BDA to identify hot spots of carbon emission so they can be reduced (Singh et al., 2019a). Additionally, customer loyalty can be improved with a BDA analysis of sentiment (Dubey et al., 2016). The company should have a BDA-based data offering structure for their customers.

Tseng et al. (2019) stated that to build successful sustainable manufacturing operations; firms should upgrade the synchronization of financial-related decisions, obtain cost information, focus on service and quality of the product, and ensure improved customer satisfaction. BDA helps reduce manufacturing process costs and the final prices of products and components. Using predictive analytics, the manufacturer can schedule predictive maintenance to prevent costly asset breakdowns and avoid unexpected downtime, leading to reduced operational costs.

Sustainable manufacturing focuses on resource optimization without compromising the productivity or effectiveness of manufacturing operations. Resource optimization refers to the optimal usage of available resources and reducing carbon dioxide emissions, harmful materials, etc., from different manufacturing processes (Piyathanavong et al., 2019). Sustainable natural resource management requires complete thought of different factors with the goal that available resources may meet the requirement of contemporary society along with future generations (Mustapha et al., 2017). Sustainable capability is the ability of firms to respond to their short-term financial objectives and future goals. A firm's sustainable capabilities include integrating complex resources to achieve sustainable goals, communicating sustained values to its stakeholders, and gaining a sustainable competitive advantage. Subsequently, organizations can create sustainable capabilities that improve performance at the ecological, environmental, and social levels by coordinating green human resources management, green supply chain management, etc.; (Amui et al., 2017). Singh & El-Kassar (2019) have observed that organizations should have an environmental policy in place, and their management should support implementing such environment-friendly practices. Table 2.1 categorizes these sustainability benefits from three perspectives of the triple bottom line approach, i.e., social, economic, and environmental. In a manufacturing organization, minimization of manufacturing time and increasing reuse of components belong to social aspects of sustainability. Economic aspects include reduction of manufacturing costs, maintenance, and recycling. Environmental factors cover reducing carbon dioxide emission, electric consumption, component packaging, and component weight (Raut et al., 2019).

2.4 Big Data Analytics Benefits

Sustainable manufacturing operations (SMOs) are a strategy for manufacturing industries that helps manufacturers in terms of reduction in the use of resources and low pollution levels for the entire lifecycle (Roy and Singh 2017). Industry 4.0 technologies can be easily integrated with business processes for sustainability. Integration results in cost reduction, sustainable process, timely information sharing, improving efficiency, flexibility, quality, and collaboration (Ali and Gölgeci, 2019; Machado et al., 2020; Lechler et al., 2019, Acioli et al;2021, Pham et al., 2019). Ye et al. (2021) considered BDA as an advanced tool for sustainable manufacturing. To achieve sustainable development, BDA addresses the grand challenges which hinder sustained efforts (Eisenhardt et al., 2016; George et al., 2016). Belaud et al. (2019) highlighted the importance of big data at different levels of sustainability, and Wu et al. (2017) encored that sustainability is an essential element for the business models of new technologies like BDA (Martinez and Mora, 2019). BDA tools are being adopted to minimize production risks, market losses, and process flaws. Use of BDA tools also increases business effectiveness (Sharma et al., 2020). BDA helps organizations in profiling their customers (Ardito et al., 2019), which further supports the organizations in satisfying their customers (Zhou et al., 2019). BDA has helped organizations increase their return on investment by 15-20%, enhance productivity, and provide a competitive advantage (Ding, 2018; Manyika et al., 2011; Zhou et al., 2019). Innovations in the industries promoting sustainability have helped organizations consume less energy, reduce waste, and improve the organization's brand value (Ding, 2018). Through BDA, the data transparency in the entire supply chain has increased and has prevented goods from being damaged (Birkel et al., 2019; Buntak et al., 2019; Junge, 2019). With the improvement in transparency, errors are minimized and losses incurred are reduced (Birkel et al., 2019; Gabriel and Pessel, 2016; Stock and Seliger, 2016).

Investment in BDA improves firm performance in terms of better economic, environmental, and social indicators. Manufacturing industries in the developed world are implementing BDA and (Dubey et al., 2016) have identified management, governing pressures, supplier relationship management, employee engagement, reconfigurable manufacturing systems, and lean manufacturing as pillars for world-class sustainable manufacturing. Thakur and Mangla (2019) investigated the change for sustainability considering operational human-technological aspects in leading Indian home appliance industries. Akhtar et al. (2019) found a significant positive relationship among data-driven activities, and organization performance. Yasmin et al. (2020) identified that BDA capabilities positively impact organizational performance. Scavarda et al. (2020) have also highlighted the importance of integrating Industry 4.0 with circular economy systems.

Liu et al. (2020) explored the contribution of advanced technologies (Internet of Things, BDA, Cloud Computing, Artificial Intelligence etc.) to the development of SMOs. Gawankar et al. (2020) found valuable insights for retail supply chain practitioners on planning BDA investments. A Big data influences the supply chain performance measures in the retail supply chain with the contractual-based alliance.

Aho (2015) argued that Big Data could develop and transform organizational cultures. Integration of big data from multiple sources has helped the organization to optimize its supply chain. Sanders (2016) observed that the application of BDA is not limited to price optimization, route optimization, inventory optimization, micro-segmentation of marketing, or labor scheduling but has extended to many other areas of Supply Chain Management. The application of BDA is further developed to boost the after-sales performance of service parts management. With the advancement of BDA, several technologies are developed that help organization extracts meaningful information from the data (Marr. B, 2021). Some recent developments include Artificial Intelligence, Quantum Computing, Edge Computing, Natural Language Processing, and Hybrid cloud. Therefore, the development in the field of BDA has been a game changer for analytics (Gill, 2021).

BDA provides potential benefits at the strategic and operational levels for sustainable manufacturing. They help in sustainable sourcing, supply chain networking, and product designing at the at the strategic end. At the operational end, they help improve visibility by providing real-time data, improving flexibility, and helping manage the volatility and cost fluctuations during manufacturing (Mangla et al. 2020). Table 2.2 summarizes the benefits of BDA for sustainable manufacturing.

Table 2.2 Benefits of Big Data Analytics

BDA Benefits	**References**
Decrease in operational cost and improvement in quality	Choi et al. (2018), Aydiner et al. (2019), Dubey et al. (2020), Ren et al. (2019), Luo et al. (2017), Rachinger et al., (2019), Machado et al. (2020; Ali (2019), Pham et al., (2019), Ozkan-Ozen *et al.*, (2020)
Real-time decision-making	Machado et al. (2020), Ren et al. (2019), Inamdar et al. (2020), Kumar et al., (2021)

Improved business transformation	Maroufkhani et al. (2020), Ren et al. (2019), Sharma et al. (2017), Arunachalam et al. (2018), Giannakis and Louis (2016), Dubey et al. (2019)
Better product/service quality	Luo et al. (2017), Shibin et al. (2017a), Choi et al. (2018), Ghasemaghaei and Calic (2019), Kazancoglu et al. (2021)
Minimization of resources/energy waste	Ren et al. (2019), Shibin et al. (2017a), Pinto et al., (2020), Rachinger et al., (2019), Banyai et al., (2019)
Improve safety and prevent risks	Luo et al. (2017), Raut et al. (2019)
Reduce or eliminate emissions from industrial processing	Ren et al. (2019), Shibin et al. (2017b)
Improvement in economic and environmental sustainability	Ren et al. (2019), Luo et al. (2017), Bag et al. (2017), Kamble et al. (2020), Belaud et al., (2019)
Effective decision-making process	Machado et al. (2020), Dubey et al. (2019) Arunachalam et al. (2018)

2.5 Barriers to Investment in Big Data Analytics

In the age of Industry 4.0, manufacturing organizations have begun to adopt BDA to optimize their decisions (Manyika et al., 2011). However, organizations are facing several challenges in making investments for BDA applications. These investment challenges are due to the limited knowledge of how to use BDA for manufacturing operations. Although BDA adoption requires high investments, it is fast changing and offers new opportunities for data handling (Schull and Maslan, 2018). Alharthi et al. (2017) presented a qualitative analysis of barriers to using BDA. The barriers to the implementation of BDA for manufacturing are categorized as organizational, data management, and human barriers. Organizational barriers have been important barriers that influence BDA implementation (Lamba and Singh, 2017; Sun et al., 2018; Moktadir et al., 2019). The important organizational barriers include security, privacy, digital infrastructure, organizational policies, etc. (Amerioun et al., 2018; Mishra & Rane, 2019; Sivarajah et al., 2017). A suitable organizational culture will help BDA implementation dramatically and reduce the risk associated with the BDA process (Diaz et al., 2018; Sun et al., 2018). Lack of management support and lack of digital vision hinder the success of BDA implementation from the organizational viewpoint. Management can encourage their employees to use the implementation of big data by designing incentive programs and connecting them to the use of big data (Watson, 2019). Human barriers include people's awareness and skills of the employees in the context of BDA (Dubey et al. 2019).

Manufacturing industries face obstacles in managing BDA due to a lack of IT experts. Data management barriers are implicit complications of BDA because of the data development, broadening of data sources, different formats, and unstructured data, making it difficult to deal with, store, and regain the data (Alharthi et al.2017). The barriers need to be investigated for the successful implementation of BDA to minimize risks, improve productivity, enhance quality, etc. Organizations that know their current state of BDA capabilities are better at overcoming the challenges associated with BDA. Maturity Models can be used by organizations to understand their present state of technology and to benchmark themselves with the industry standards further. Manufacturing industries are increasingly turning to big data analytics to make decisions based on big data. However, many barriers exist to adopt BDA in sustainable manufacturing operations (Moktadir et al., 2019). If you want to reduce risks and boost productivity, quality control, decision making abilities, etc., then you should look into removing these roadblocks to using BDA solutions. A better understanding of these obstacles would aid the reader in formulating strategic and tactical plans for implementing BDAs. Better tactics can be developed by manufacturing organisations if the obstacles to BDA are first well explored. The following are discussions of major barriers identified in the literature.

- ***Lack of policies for data security and privacy:***

As organizations increasingly have access to confidential consumer data in the present Industry 4.0 era, information and cyber security issues arise. Although there is strict intra-organizational regulation over access to personal information, customers may be concerned about data security (Kache and Seuring, 2017). Data privacy and security are the common issues for investment in BDA (Maroufkhani et al., 2020). Data must be secure if organizations compete in the global market (Alharthi et al., 2017; Delen and Ram, 2018). Jensen and Remmen (2017) have observed that confidentiality must be maintained among all the stakeholders while sharing the data. There is a lack of policy framework which can give confidence to investors. Unethical use of big data and ineffective data processing lead to privacy and security concerns. The lack of policies and outdated regulations has been a big hurdle while data is shared, especially when it comes to consumer data. Lack of policies becomes a major hurdle for multinational organizations as they are obliged to abide by several countries' regulations sharing data across their worldwide supply chains (Alfaro et al., 2015). This barrier should be minimized by framing suitable policies for all stakeholders.

- ***Absence of data-driven decision-making culture:***

Data-driven culture and employees are key components in learning and knowledge retention. Decisions are better if taken based on information extracted from the data. However, collecting data for proper analysis is a complicated task for manufacturers (Kamble and Gunasekaran 2020). Manufacturers should develop data-driven decision-making culture to deal with this barrier (Gupta et al., 2020). Data transparency and accountability should be nurtured to create a data-driven culture (Malomo and Sena, 2017). In addition, the role of big data service providers can be extended to influence the attitude and decisions of top management regarding BDA (Lai et al., 2018). The unavailability of suitable big data services discourages organizations from investing in BDA.

- ***High cost of developing digital Infrastructure:***

Developing a digital infrastructure is a prime requirement for implementing BDA for manufacturing organizations (Belhadi et al., 2019). Data infrastructure plays a vital role in implementing BDA or BDA-enabled architecture (Kim et al., 2014; Barbierato et al., 2014). This infrastructure requires hardware, software systems, and various tools to collect, process, and analyze data. The architecture should be dynamic and smart, which supports the scalability of a large amount of data. In addition, the architecture should support different sensors used under analytical tools (Raut et al., 2019; Dubey et al., 2021).

However, developing digital infrastructure organizations requires a high investment (Sivarajah *et al.*, 2017; Wang and Wiebe, 2016). Therefore, the high cost of digital infrastructure is a major problem for the organization. Moreover, problems in high-speed internet access severely impact the implementation of emerging technologies (i.e., BDA/Industry 4.0) in manufacturing industries.

- ***Ineffective performance framework for assessing the effectiveness of investments in new technologies:***

There are several challenges that organizations face in implementing new technology. However, the managers are well qualified and experienced in leading a team to develop new technical innovations but face several challenges in its implementation (Belhadi et al., 2019; Alharthi et al., 2017). There is inadequate performance measure in practice to check the implementation of new technology. It is the responsibility of organizations to ensure that the effectiveness of new technology obtains organizational goals which are essential for their growth.

- ***Rigid organizational culture for making new investments in technologies:***

Organizational culture plays a important role in the execution of new technologies. Culture is the implicit norm that defines employee behavior. The rigid and reluctant organizational culture is a major obstacle to investment in new technologies. Conventional organizational culture lacks flexibility and is quite averse to change (Jahanshahi and Brem, 2017). A radical shift is required in the organization's culture to invest in new technologies and focus on all levels of the organization (Seth *et al.*, 2018). Therefore, organizations need to build a flexible culture to invest in new technologies that allow individuals of various specialties, expertise, and skills to access the same information and to encourage each other in all aspects of work (Kalema et al. 2016).

- ***Lack of confidence in return on investment in BDA implementation:***

Return on investment refers to the ratio of net profit to the cost of investment in BDA implementation. In other words, it measures the return on a specific investment relative to its cost. Justifying and estimating the RoI is a challenge to BDA implementation (Frizzo-Barker et al., 2016). The gap between investment in big data and its return is important and should be reduced (Delen and Ram, 2018; Schull and Maslan, 2018). The return on investment is challenging for BDA as this highly depends on the "downstream" employee, who is responsible for executing the task.

- ***Lack of research on applications of BDA tools:***

The research on applications of BDA tools is the key to developing new technologies that may process the voluminous data for meaningful inferences. The manufacturing industries hesitate to invest in new technologies for BDA implementation as there is limited research on the application of BDA tools (Belhadi et al., 2019).

- ***High cost associated with managing massive unstructured data:***

Organizations require huge investment costs in implementation and managing an unstructured high volume of data to control their data and provide more security (Schull and Maslan 2018). Organizations see data governance as a major challenge in most cases. Although there are advancements in cloud computing technology and hardware equipment, organizations are still facing problems with data storage, its management, and mainly extracting valuable information from the data at a lower cost (Sivarajah *et al.*, 2017). Therefore, organizations are unwilling to invest in BDA due to the high cost of managing unstructured data.

- ***Unavailability of specific BDA tools as per industry requirements:***

Popular BDA tools including as Hadoop, MapReduce, Spark, Flink, etc. share a lot of similarities in their features and capabilities. Organizations have a hard time determining if BDA tools are appropriate for their needs. If you thought handling massive data was difficult, try processing unstructured or semi-structured data. (Maroufkhani et al., 2020; Kaisler et al., 2013; Raut et al., 2019). The manufacturing sector has unique needs for BDA tools to handle large data. But there is a dearth of adequate hardware and software**.**

- ***Absence of coordination among stakeholders for investing in BDA-related activities:***

A stakeholder viewpoint is important to provide the required framework for a shift toward new technologies (Moktadir et al., 2019; Malomo and Sena, 2017). Flexible stakeholder management is the key to developing a competitive strategy in terms of cost, quality, and timings (Aboelmaged, 2014; Barzegar et al., 2018). It also includes an awareness of their current interests and coordination among stakeholders in adopting BDA. According to Zhou et al. (2019), the lack of participation of the stakeholders hinders the decision-making process for attaining sustainability. The coordination among stakeholders is important as there is often a shortage of time for checking the results of BDA, which might take up to 12 to 18 months. Because of this, BDA needs constant support from all the top management teams, including all the organization's key stakeholders. Therefore, there is a need for collective action on the part of all major stakeholders falling in the ambit of the BDA implementation framework. However, this aspect is lagging currently.

- ***High cost associated with integrating data across the supply chain:***

BDA requires investment in IT infrastructure, employee skill training, and analysis tools (Ahmed et al.,2018; Schull & Maslan, 2018; Sun et al., 2018). While the high price of information technology is decreasing, the cost of business development analysis remains high (Sivarajah et al., 2017). Organizations are hesitant to invest in BDA because of the hefty price tag involved with integrating data across the supply chain.

- ***Inadequate data sharing policy among stakeholders:***

Existing data processing applications and database management systems still have a long way to go before they can efficiently handle and exchange massive amounts of data. (Jiang et al., 2015). While forming a cross-functional team to implement BDA, organizations have an inadequate data sharing policy, leading to principle-agent conflicts and inappropriate incentive arrangements within the network. However, there is still no appropriate legal framework to regulate data sharing among stakeholders. Leaders play an important role at this stage. There should be an effective use of BDA to create value for the firms.

- ***Lack of competence in using BDA in resource optimization:***

Oftentimes, businesses lack the necessary expertise to implement BDA-related new technology. Employees' skills to embrace BDA technology are hindered by a lack of proper training programmes. According to Gupta et al. (2019), the implementation of BDA is hindered by a lack of managerial and technical expertise in big data predictive analytics. Because supply chain partners have inadequate resources, they are unable to communicate data and extract information in real time, which prevents organisations from optimising their use of those resources to their full potential. For BDA to be successful, there must be close cooperation and coordination between the various cross-departmental groups within an organisation.

- ***Lack of support from employees for implementing new technologies:***

Organizations need to be able to update their tool regularly to remain competitive and ensure that these changes are accepted by their employees (Moktadir et al., 2019). Sometimes the ambiguity about what modern technology entails for employees creates resistance to getting the new technologies. Organizations face problems investing in new technology without proper employee management and training (Gawankar *et al.*, 2020).

- ***High cost of hiring skilled BDA consultants:***

BDA requires highly skilled professionals (Kim et al., 2014; Barbierato et al., 2014). Some organizations hire consultants as advisors on various issues, including new technologies, hardware, and software. However, engaging such experts to involve a high cost becomes an obstacle for organizations to invest in BDA (Alharthi et al., 2017). Therefore, due to a lack of financial readiness to cover the cost of BDA, investment in BDA may lead to failure (Alalawneh and Alkhatib, 2021).

- ***High cost of training programs on BDA:***

The employee must be well versed with new technologies. Organizations are facing the problem of a lack of big data skills in their employees. This is due to the lack of effective training programs and employees' less involvement and interest in modern technologies (Oncioiu et al., 2019). The employees should be ready to update their knowledge in their areas through training and workshops (Raut et al., 2019; Dubey et al., 2019; Akter et al., 2016). However, the cost incurred for these training and workshops is higher.

The skill training programs on BDA require high costs deterring organizations from investing in such programs due to fear of inadequate returns. To address the problem, all IT leaders should come together to work and develop new strategies to address the issues of BDA. Without proper training, the potential of modern technology cannot be fully tapped.

- ***Lack of trust and commitment among employees:***

The employee's trust and commitment play an important role in successfully implementing any new technology in an organization (Zhang et al., 2017). Employees have a pervasive fear of change that automation of their particular work process may lead to their retrenchment. They fear losing a competitive advantage and lack trust due to the sensitivity of the data. Therefore, trust and commitment among employees are crucial barriers to invest in BDA. Supportive leadership plays a significant role in removing employees' fear regarding the change (Schull and Maslan, 2018).

The literature review reveals that many studies have been done on the usage of big data services, focusing mostly on how users perceive the advantages, costa, and data quality (Shin, 2016). (Shin, 2016). In this context, no comprehensive review is available where an analysis of barriers to BDA implementation in different manufacturing processes has been considered. Manufacturing industries are unaware of the maturity level of BDA or whether the organization's current capabilities are sufficient for implementing a BDA (Verma, 2017). Table 2.3 summarizes barriers that were identified through an extensive literature review and based on the opinion of experts from industry and academia.

Table 2.3 Barriers for Investment in BDA for Manufacturing

Abbreviation	Barriers	Reference
B-1	Lack of policies for data security and privacy	Alharthi et al., (2017), Oncioiu et al., (2019), Malomo and Sena (2017), Jensen and Remmen, (2017), Alfaro et al., (2015)
B-2	Absence of a data-driven decision-making culture	Malomo and Sena (2017), Zhang et al. (2017), Kamble and Gunasekaran (2020), Gupta et al., (2020), Lai et al. (2018)
B-3	High cost of developing digital Infrastructure	Maroufkhani et al. (2020), Sivarajah et al., (2017), Alharthi et al., (2017), Belhadi et al., (2019) Kim et al., (2014), Barbierato et al., (2014)

B-4	Ineffective performance framework for assessing the effectiveness of investments in new technologies	Oncioiu et al., (2019), Belhadi et al., (2019), Schull and Maslan (2018)
B-5	Rigid organizational culture for making new investments in technologies	Schull and Maslan (2018), Kamble et al. (2020a), Seth et al., (2018)
B-6	Lack of confidence in return on investment in BDA implementation	Oncioiu et al.,(2019), Moktadir et al., (2019), Schull and Maslan (2018)
B-7	Lack of research on applications of BDA tools	Belhadi, et al., (2019), Arunachalam et al., (2018)
B-8	High costs associated with managing massive unstructured data	Schull and Maslan (2018), Belhadi et al., (2019)
B-9	Unavailability of specific BDA tools as per industry requirements	Maroufkhani et al. (2020), Raut et al., (2019), Dubey et al. (2021)
B-10	Absence of coordination among stakeholders for investing in BDA-related activities	Zhou et al., (2019), Aboelmaged, (2014), Barzegar et al., (2018), Moktadir et al. (2019), Malomo and Sena (2017)
B-11	High cost associated with integrating data across the supply chain	Maroufkhani et al., (2020), Raut et al., (2019), Arunachalam et al. (2018)
B-12	Inadequate data sharing policy among stakeholders	Janssen et al., (2017), Mishra and Rane (2019)
B-13	Lack of competence in using BDA in resource optimization	Mazzei and Noble (2017), Janssen et al., (2017), Raut et al., (2019)

B-14	Lack of support from employees for implementing new technologies	Maroufkhani et al. (2020), Moktadir et al., (2019)
B-15	High cost of hiring skilled BDA consultants	Oncioiu et al., (2019), Dubey et al. (2016), Malomo and Sena (2017), Alharthi et al., (2017), Raut et al., (2019), Dubey et al., (2019), Kim et al., (2014), Barbierato et al., (2014)
B-16	High cost of training programs on BDA	Malomo and Sena (2017), Oncioiu et al., (2019) , Kamble et al., (2020) Raut et al., (2019); Dubey et al., (2019)
B-17	Lack of trust and commitment among employees	Schull and Maslan (2018), Zhang et al., (2017)

2.6 Identification of Critical Success Factors for Big Data Analytics Implementation in Manufacturing

Critical success factors are defined as the attributes required to ensure overall success for an organization. In other words, critical success factors include issues vital to an organization's current activities. Based on the literature review, several critical success factors are identified. These critical success factors are listed in Table 2.4 with their brief description. Many organizations in developing countries have limited access to technology, funds, infrastructure, and skilled labor. However, this is not the case with most organizations in developed countries (Kumar et al., 2021). Therefore, the critical success factors may be different for developing countries from developed countries. The literature review reveals that much work has been reported on applying BDA, particularly in developed countries. Many organizations in developing countries are still struggling to leverage the benefits of BDA applications to improve their performance from a sustainability perspective. Manufacturing organizations are showing reluctance toward technological changes happening in the market simultaneously.

Table 2.4 Critical Success Factors for Big Data Analytics Applications

Critical Success factors	Description	Reference
Development of contract agreement among all stakeholders	Ensures confidence in big data usage among stakeholders and defines responsibilities and procedures for better communication.	Janssen et al. (2017), de Camargo et al., (2018)
Commitment and engagement of top management	Top management will guarantee resource mobilization and its attention to BDA implementation.	Gupta et al. (2018), de Camargo et al., (2018), Dubey et al., (2016), Ivanov et al., (2019)
Development of capability for handling big data	Deployment of accurate tools and techniques for analysis, visualization, and processing of big data	Janssen et al., (2017), Yaqoob et al., (2016), Dubey et al., (2019), Wilcox et al. (2019)
Robust cybersecurity system	Refers to the maintenance of privacy and security of data. Its absence may lead to financial loss and damage a firm’s reputation.	Lee (2017), Ivanov et al., (2019)
Coordination among big data stakeholders	Cooperation is needed to change the mindset of all stakeholders against the notions that BDA tools require huge investment and extra efforts	de Camargo et al., (2018), Wilcox et al., (2019)
Problem identification and solving capacity	Capabilities in terms of resources, including human, technology, capital, etc., to ensure conversion of inputs into higher value outputs	Janssen et al., (2017), Dubey et al., (2019)

Process integration and institutionalization	Capacity to coordinate procedures to institutionalize assignments/ information that brings improvement in the big data chain. In other words, this is an imperative condition for institutionalizing and reutilizing the utilization of big data.	Janssen et al., (2017), Gupta et al., (2018)
Flexible digital infrastructure	In-house resources for data acquisition, data processes, and data analysis	Cui et al. (2020), Duan et al. (2019), Ivanov et al. (2019)
Strategy development for BDA	The actions taken to ensure that the strategic planning is carried out	Janssen et al., (2017), Gupta et al., (2018), Gupta et al., (2020)
Availability of quality and reliable big data	Ensuring appropriate and accurate data for the for the intended use	Janssen et al., (2017), Duan et al., (2019), Wilcox et al., (2019)
Knowledgeable and capable decision-makers	Experienced decision-makers who easily understand and analyze big data are required for quick and better decisions.	Del Fabbro and Santarossa (2016), Cui et al., (2020)
Data-driven organization culture	It takes a tremendous amount of effort to change a culture, so most of the authoritative apparatuses for altering behaviour should be used.	Janssen et al., (2017), Duan et al., (2019), Weerakkody et al., (2017), Cui et al., (2020)
Process monitoring and control	Refers to data processing-related hardware and software systems	Dubey et al., (2021), Duan et al., (2019)

Integrating customers' requirements with performance framework	Data aid in reducing fraud and enhance industry performance and decision-making capacity.	Dubey et al., (2019), Janssen et al., (2017), Gupta et al., (2020)
Responsive information sharing framework	An evaluation of the indirect benefits of information technology is provided by the relationship between information system framework and industry performance.	Duan et al., (2019), Dubey et al.,(2021)

2.7 Research Gaps

BDA is a relatively new concept in the Indian manufacturing industry, and it requires a lot of care and nurturing at this point. The manufacturing sector is aware of BDA but has not yet properly implemented the notion. In the context of India's manufacturing sector, only a small number of research have been conducted on the subject. Research done till now has mainly targeted the service sector (Tormay, 2015) rather than the manufacturing sector. There is a lack of research that examines the effects of implementing BDA in manufacturing processes on operational performances within the setting of India's manufacturing sector. Doing the study that provides a foundation for BDA application in manufacturing is essential for filling in many knowledge gaps. This study sets out to solve these gaps by providing a framework, using a variety of descriptive and inferential statistical studies on a subset of the Indian manufacturing sector, that may be used to better manage the overall performances of these sectors.

Researchers have not thoroughly examined the capabilities of BDA for sustainable manufacturing processes, according to Belhadi et al. (2019). Aside from that, research on applying BDA in the manufacturing sector in developing nations like India is limited. Many businesses are still functioning in silos and are not automating their processes by industry 4.0. This creates a research gap for the current study's topic, which analyzes the critical success factors in implementing I4.0 technologies like BDA to reach a long-term operational goal. The outcomes of this study will have a beneficial impact on the successful implementation of BDA in manufacturing operations and will encourage industry professionals to invest in BDA as a top priority. Manufacturing companies face significant obstacles in adopting modern technology to maintain long-term operations (Singh et al., 2019). As a result, to make manufacturing operations more sustainable, this study explores critical success factors for applying BDA in the manufacturing sector.

The observations and gaps regarding BDA in the field of manufacturing, based on the literature review are highlighted below.

- There is lack of comprehensive and exhaustive study on implementation of Big Data Analytics to manufacturing sector in Indian context.
- There is limited work on challenges in adoption of BDA in manufacturing sector.
- There are limited studies available analysing the CSFs in BDA implementation in the context Indian manufacturing sector.
- There is lack of empirical study on determinants for adopting BDA in the Indian Manufacturing scenarios.

2.8 Research Objectives

The objective of this study is finding out the many applications, important success factors, and challenges to adopting BDA in manufacturing operations to improve the operational performance of the Indian Manufacturing Industries. The purpose of this thesis is to assess the usefulness of BDA within the framework of India's manufacturing sectors. The primary aims of this study are listed below; they were determined based on the research gaps identified above:

1. Identification and Justification for benefits of BDA applications in the context of the Indian Manufacturing Industry.

2. Identification and Analysis of major barriers obstructing the implementation of BDA and develop framework for evaluating the barriers intensity index.
3. Identification and ranking of Critical Success Factors in BDA implementation
4. Exploring the determinants and develop a conceptual framework for adopting BDA in the context of Indian Manufacturing.

2.9 Chapter Summary

The literature pertaining to the study is reviewed extensively in this section. Literature review methodology is described. The first step has been a thorough examination of BDA's setup and context. Research and expert opinion have been used to identify other CSFs to BDA implementation in manufacturing, as well as the benefits of BDA, barriers to investment in BDA, and hurdles to BDA implementation in other industries. The research gaps and motivation for this study are discussed. Following an analysis of research gaps, we present list of research objectives. The next chapter provides an in-depth discussion of the research methodology used for the study.

CHAPTER 3

RESEARCH METHODOLOGY

The structure of this chapter is as follows: “Introduction” section provides introduction of this chapter. In “Factor Analysis” section, factor analysis is discussed. “Graph theory matrix approach” section deals with Graph theory matrix approach. “Analytics hierarchy process” section Analytics hierarchy process is discussed. “Fuzzy TOPSIS” section provides the detail of fuzzy TOPSIS. “Decision-Making trail and Evaluation Laboratory (DEMATEL)” section presents DEMATEL approach. “Empirical Analysis” section deals with the empirical analysis. Finally, the summary of this chapter is provided in “Chapter Summary” section.

3.1 Introduction

Research methodology refers to a set of techniques used to address a particular research issue. The purpose of this document is to serve as a blueprint for future studies. Using appropriate research methods, scientists constantly strive to enhance the credibility of their findings. The research questions are outlined at the start of this chapter. The remaining sections of this chapter will provide a detailed explanation of the research technique used in this study. The structure of this chapter is shown in Figure 3.1.

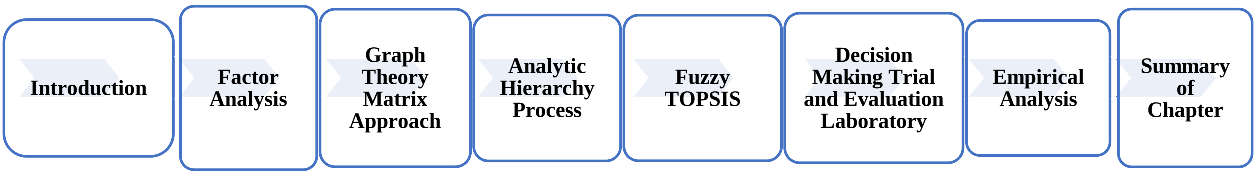

Figure 3.1 Chapter Flow Diagram

A research technique is a set of procedures for conducting a study. The purpose of this document is to serve as a blueprint for future study. Researchers constantly strive to enhance the quality of their results in their study domains by applying appropriate research procedures. The research questions are presented at the outset of this chapter. A detailed description of the methods used in this study will be provided in subsequent parts. An outline of this chapter's structure is shown in Figure 3.1. The BDA adoption in the manufacturing sector is investigated through the following questions:

RQ1: What are the benefits of BDA applications to ensure its implementation in manufacturing?

RQ2: What are the key barriers to investment in BDA?

RQ3: What are the CSFs for implementation in the manufacturing sector?

RQ4: What are the determinants of BDA adoption in the manufacturing sector?

To find answers to these questions, different benefits of BDA applications, barriers, critical success factors in investment in BDA have been identified in Chapter 2. In response to these research questions, the different multicriteria decision-making (MCDM) approaches are used in the current research. The research framework is shown in Figure 3.2.

3.2 Factor Analysis

The descriptive analysis for the selection of important barriers based on descriptive measures and exploratory analysis for the categorization of barriers is done using factor analysis. Factor analysis is a technique to identify groups of factors related to a specified category. It is a statistical method that represents the relationships among a set of observed characteristics in terms of common factors. Factor analysis was employed *to* find the number of categories of barriers and merge the BDA barriers into a respective category. Factor analysis is a widely used technique for data reduction and the construction of measurement scales. Rajput and Singh (2019) applied the factor analysis to understand the relationship between the circular economy and industry 4.0. Raut et al. (2019) have used this approach to link BDA and operations for sustainable business management. Li et al. (2019) applied factor analysis to study the water-energy-food nexus conundrum. There are seven basic steps to performing factor analysis (DeCoster, 1998).

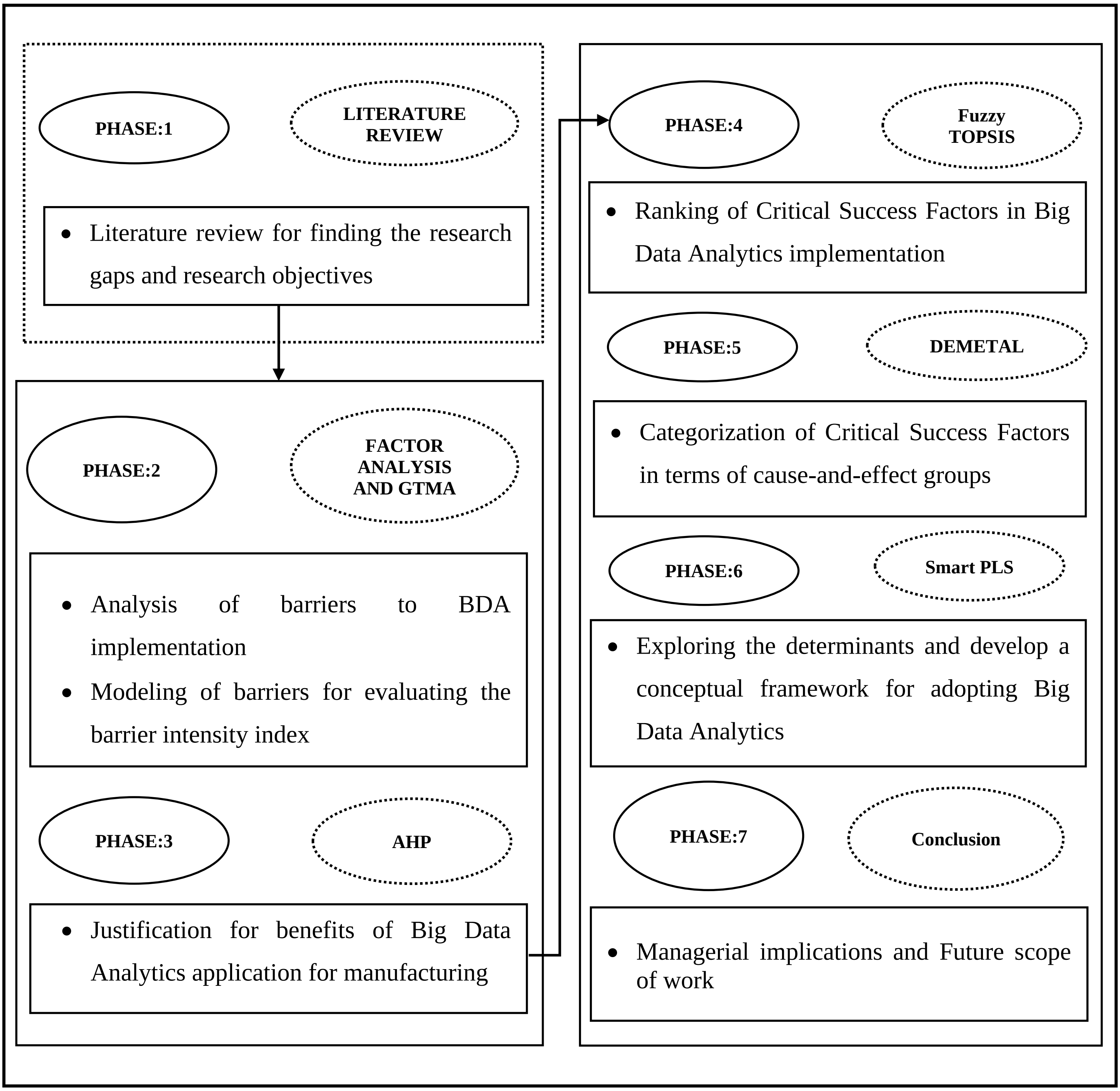

Figure 3.2 Research Framework (Source: Self)

3.2.1 Factor Analysis Procedure

In this study, factor analysis is employed to find the number of categories of barriers and merge the BDA barriers into a respective category. There are seven basic steps to perform factor analysis. These are briefly detailed below:

Step1. Collect data

The data is collected through responses from experts on a questionnaire designed for this purpose.

Step2. Data validation and reliability check

Homogeneity, Internal consistency, and sampling adequacy check are performed as per discussion in Section 4.2.

Step3. Select the number of categories for barriers

The eigenvalue is calculated to determine the number of categories of barriers. The number of categories equals the number of extractions with an eigenvalue greater than one.

Step 4. Extraction of barriers into the respective category

For extraction of barriers into respective categories, principal component analysis (PCA) is used. PCA reduces the dimensionality of a dataset with numerous interrelated variables.

Step 5. Rotate factors to find a final solution

Factor rotation aims to rotate the factor matrix to achieve a simple structure to improve the interpretability of the factor solution. Factors are rotated for an explanation to find a stingy solution in that each variable receives a considerable contribution, i.e., factor loading, from only one factor.

Step 6. Interpret factor structure.

After determining the number of factors, examine the loading pattern to determine the factor that influences each variable most.

Step 7. Construct factor scores for further analysis.

Based on the Exploratory factor analysis (EFA) results, barriers are classified into three categories. Further, GTMA is applied to find the intensity of extracted barrier category.

3.3 Graph Theory Matrix Approach

The graph theory matrix approach (GTMA) is a valuable tool for decision-making that has been used widely. GTMA has the power to solve some complex problems and has been applied in various applications. Bhandari et al. (2019) used GTMA to evaluate barrier intensity in implementing cleaner technologies. Singh and Kumar (2019) applied the GTMA approach for deriving a flexibility index for a supply chain. Singh et al. (2019a) employed GTMA to evaluate the supply chain coordination index. Agrawal et al. (2016) and Kumar et al.(2017) applied the GTMA approach to assessing reverse logistics strategies and maintainability. Gupta et al. (2017) and Agrawal et al. (2016a) applied GTMA to propose a disassembly index in automotive systems and examine outsourcing decisions, respectively. This approach was also used to predict the acute ecotoxicity of chemical substances (Takata et al., 2020).

GTMA is a suitable tool for quantifying the impact of the barriers as it has been used for similar applications. Therefore, it is applied in this study. In the GTMA application, initially, a relative importance matrix is developed. A 10-point scale for relative significance of attribute (r_{ij} 's) is employed (Muduli et al., 2013). The data is collected in the form of responses to a questionnaire from experts.

Once the BDA barriers are identified, the relative priority of the i^{th} barrier over j^{th} (r_{ij}) is taken as per scale. Here, the value 1 denotes very low. and 5 indicates very high relative importance. The relative importance matrix is further used to calculate the index value of the individual category of barriers. Finally, the overall barrier intensity for investment in BDA is evaluated. A stepwise procedure of the Graph Theory Matrix Approach is detailed in the following subsection:

3.3.1 Procedure Graph Theory Matrix Approach

The main steps for applying Graph Theory Matrix Approach are as follows:

i) Identify barriers affecting the investment in BDA for sustainable manufacturing operations and categorize barriers into some groups.
ii) Construct the digraph based on interdependencies among various categories.
iii) Construct a subsystem digraph and permanent matrix for the different categories of barriers. Compute permanent function value for each category of barriers.
iv) Construct an inheritance and interdependency matrix for barriers by taking the expert's opinion.
v) Calculate the index value of the different categories of barriers based on the permanent function value of different types of barriers and their interdependencies.

3.4 Analytic Hierarchy Process

The AHP-based methodology is proposed to justify BDA application for sustainable manufacturing operations. It is a Multi-Criteria Decision Making (MCDM) approach to solve complex decision-making problems. The AHP approach was developed in 1972 (Saaty, 1980). This is selected because it is easy to use and highly applicable in MCDM procedures.

MCDM procedure is a decision-making methodology where various alternates are ranked based on different criteria. Popular MCDM tools are AHP, TOPSIS, VIKOR, etc. AHP was used for decision-making for flexible manufacturing system supply chain justification in Small and medium enterprises (SMEs), prioritizing the factors for coordinated supply chain and microalgae cultivation systems (Singh 2012, 2013; Tan et al., 2017).

3.4.1 Analytic Hierarchy Process Procedure

AHP is a hierarchical process, three levels are considered for this work. The goal of problem, benefits, and alternatives, i.e., big data-enabled manufacturing (BDM) and without big data-enabled manufacturing (WBDM). These are placed at the hierarchy's first, second, and third levels. The solution procedure passes through structural hierarchy development, construction and development of comparative judgments, and synthesis of priorities and consistency calculation. In structural hierarchy development, an analytic hierarchy model for a given problem was built, as shown in Figure 3.3.

This problem aims to justify the application of BDA in the manufacturing sector, which is at the top level. The main factors in the present context are the benefits of BDA application in the manufacturing industry are placed on the second level of the hierarchy. The justification of BDA is analyzed based on its benefits. At level 3, the last level of the hierarchy, two alternatives, namely, big data-enabled manufacturing (BDM) and without big data-enabled manufacturing (WBDM), are positioned as these are the outcomes.

In the construction and development of comparative judgments, the priorities of elements are determined at every level. A pair-wise comparison matrix (nxn), P_1 for all benefits of BDA is constructed based on Saaty's nine-point scale (Saaty, 1994) as given in Appendix A1, and it is expressed as:

$P_1 = \left[a_{ij} \right]_{nxn}$ Where a_{ij} is the relative importance i^{th} factor w.r.t. j^{th} factor

$$a_{ij} = \begin{Bmatrix} 1 & When\ i = j \\ \dfrac{1}{a_{ji}} & When, i \neq j \end{Bmatrix}$$

In each pair, the more significant advantage is highlighted. The goal is to acquire linguistically specific comments from experts and then translate those into crip values. Each column of the matrix P1 is then normalised by dividing its entry by the sum of its columns. Denoted by Na_{ij} and a_{ij}, respectively, are the normalised value and pairwise comparison value of the ith criterion with regard to the j^{th} criterion. Where (i=j=7) is the number of rows and (j=i) is the number of columns in the pair-wise comparison matrix for the criteria. The normalised matrix $Na_{ij,}$ is expressed as: $Na_{ij} = \dfrac{a_{ij}}{\sum_{i=1}^{n} TC_{ij}}$. Where $TC_j = \sum_{i=1}^{n} a_{ij}$. TC_j is the total for J^{th} column.

Further, the normalized matrix (n X n) is used to obtain a priority vector matrix (Principal matrix), P_2 (n X 1), by taking the average of each row. The matrix P_2 is a column vector where the element indicates the weight of each benefit. The matrix, P2, is expressed as:

$$P_2 = \frac{\sum_{j=1}^{n} Na_{ij}}{n}$$

To check whether the expert responses are consistent, calculate the consistency ratio (CR) of the pairwise comparison matrix. In order to calculate the consistency ratio, we use the pair-wise comparison matrix, designated by P_1, and the primary matrix, denoted by P_2.

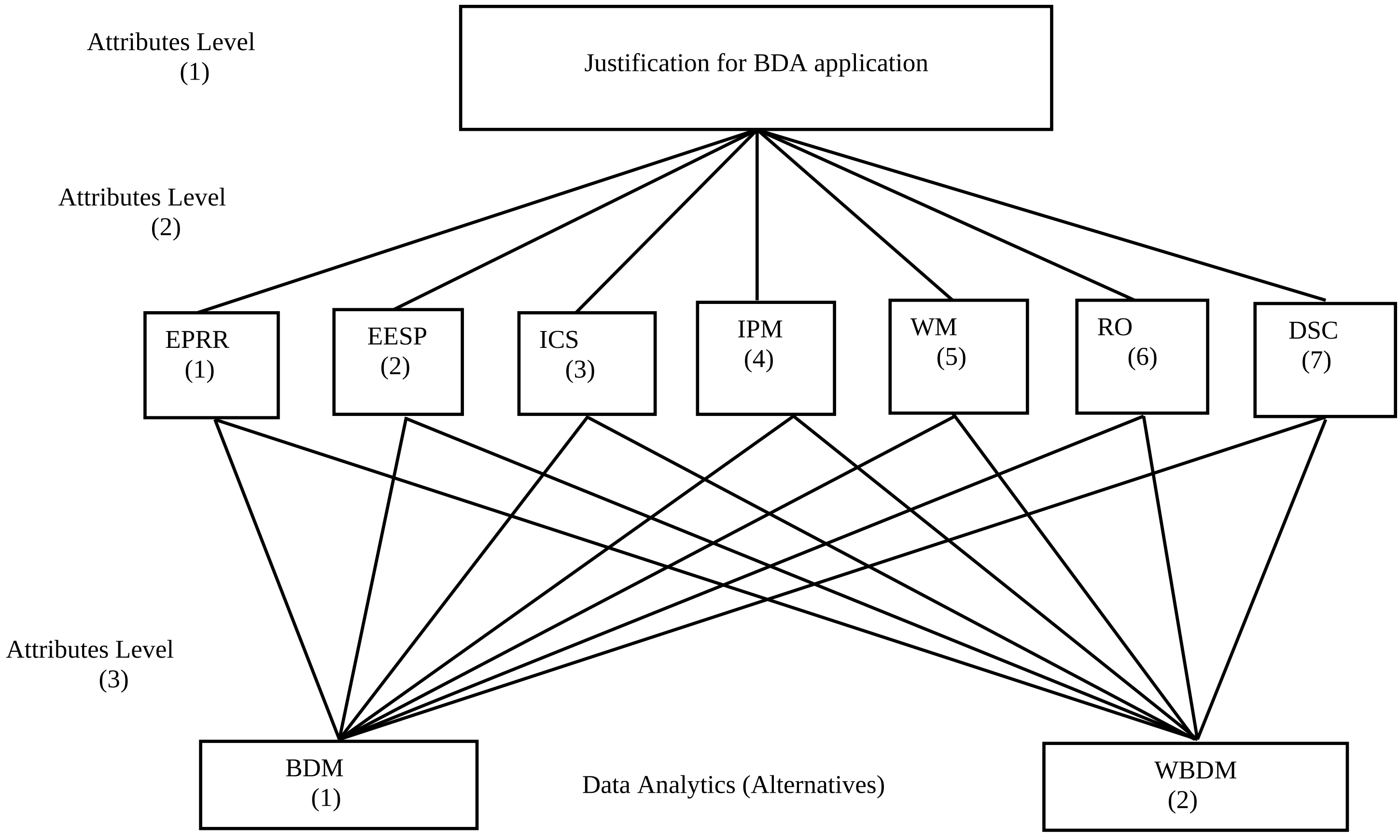

Figure 3.3 Schematic of the Analytic Hierarchy Process (Source: Self)

Further, P_3 and P_4 matrices are constructed for performing the consistency check and Priority weight of i^{th} criteria and these are expressed as Equation 3.1 (Singh 2012).

$$P_3 = P_1 * P_2 \text{ and } P_4 = P_3 / P_2 \tag{3.1}$$

Next, $\lambda_{\max} = \sum_{i=1}^{n} \frac{p_4}{n}$ is evaluated by the average of the P_4 matrix value, and then the consistency index (CI) is calculated as per Equation 3.2

$$CI = \frac{\lambda \max - n}{n-1} \tag{3.2}$$

Where n is the size of the matrix

The ratio of consistency index (CI) to random consistency index (RCI) is known as the consistency ratio, which is expressed as per Equation 3.3

CR = CI/RCI (3.3)

Where RCI value is taken as per Appendix A2.

If CR value is less than 0.1, decisions are considered consistent. For a CR value more than 0.1, the nature of decisions ought to be revised until the CR value reaches a consistent range.

The acceptable CR value depends on the matrix size, it is 0.1 for matrix sizes 4x4 and larger (Saaty 2000). Suppose the value of consistency ratio is equal to or less than the permissible value. In that case, it suggests that the assessment within the matrix is satisfactory or shows a good level of consistency in the relative decisions. A similar procedure is followed for the last hierarchy for computing the weights of BDM and WBDM for each benefit.

3.5 Fuzzy TOPSIS

Fuzzy TOPSIS is used to prioritize the most important features of BDA applications for manufacturing processes. Fuzzy TOPSIS has been utilized by a number of studies in order to prioritize strategic aspects for reverse logistics, examine disposition strategies in reverse supply chains, make disposition judgements, and analyse environmental sustainability (Agrawal et al., 2016; Singh and Agrawal, 2018; Samaie et al., 2020). This technique was also used to the processes of choosing suppliers, assessing third-party logistics providers, and outsourcing logistics operations (Kumar and Singh 2012; Junior et al. 2014). Unlike the TOPSIS approach, where crisp values are acquired, the fuzzy TOPSIS method collects data in linguistic terms for chosen alternatives for the selected criteria. Fuzzy TOPSIS is a simple, realistic form of modeling and compensatory method that includes and excludes alternative solutions based on cut-off (Singh and Agrawal, 2018). Additionally, it is a computation process that can be easily programmed into a spreadsheet that contains data on a scalar value. The data represents both the best and worst alternatives at the same time, a sound logic that explains the justification for human decision-making and all available alternatives may be on polyhedron (Kim et al. 1997). Moreover, the integration of fuzzy will further increase its strength as it can handle vague and uncertain information (Zimmermann 1985). These benefits of fuzzy TOPSIS make it a better choice among MCDM approaches.

3.5.1 Procedure of Fuzzy TOPSIS Approach

The step-by-step procedure of fuzzy TOPSIS is detailed below:

Step1: Collect the data through the survey method in linguistics form. The experts should be asked to select the best option. The options are expressed in linguistic terms for a given question. A 5-point scale with the linguistic terms low (L), fairly low (FL), medium (M), fairly high (FH), and high (H) is generally used in the questionnaire. Once the data is collected in linguistic terms, the same is converted into fuzzy numbers.

Step 2: A fuzzy decision matrix is derived based on the data collected in step 1 and converted into triangular fuzzy numbers.

$$D = \begin{bmatrix} Y_{11} & Y_{12} & \dots & Y_{1j} & \dots & Y_{1n} \\ Y_{21} & Y_{22} & \dots & Y_{2j} & \dots & Y_{21} \\ \dots & \dots & \dots & \dots & \dots & \dots \\ Y_{i1} & Y_{i2} & \dots & Y_{ij} & \dots & Y_{in} \\ \dots & \dots & \dots & \dots & \dots & \dots \\ Y_{m1} & Y_{m2} & \dots & Y_{mj} & \dots & Y_{mn} \end{bmatrix}$$

Where, $Y_{ij} = (d_{ij}, e_{ij}, f_{ij})$ is a triangular fuzzy number for the linguistic term allocated by the i^{th} respondent to the j^{th} factor. i = 1, 2, ……………..., m are the number of respondents, and j = 1, 2, ……………..…, n is the number of factors (Critical Success factors). Table 3.1 shows the scale of triangular fuzzy numbers used for each linguistic term.

Step 3: A fuzzy decision matrix (D) is converted into a fuzzy unweighted matrix (R) using the following relationship(Singh and Agrawal 2018) refer Equation 3.4.

$$R = [r_{ij}]_{m\times n;} = \left(\frac{d_{ij}}{c^*_{j^*}}, \ \frac{e_{ij}}{c^*_j}, \ \frac{f_{ij}}{c^*_j}\right) \text{ and } R = [r_{ij}]_{m\times n;} = \left(\frac{d^-_j}{d_{ij}}, \ \frac{d^-_j}{e_{ij}}, \ \frac{d^-_j}{f_{ij}}\right) \quad (3.4)$$

For benefit criteria, $c^*_{j^*} = \max_i c$ *and* for cost criteria, $d^-_j = \min_i d_{ij}$

Table 3.1 Scale for Linguistic Terms

Linguistic Terms	Fuzzy Numbers
Very low	(0.0, 0.1, 0.3)
Low	(0.1, 0.3, 0.5)
Medium	(0.3, 0.5, 0.7)
High	(0.5,0.7,0.9)
Very High	(0.7, 0.9, 1)

Step 4: Evaluate the weighted normalized decision matrix (V) using Equation 3.5 (Singh and Agrawal 2018).

$$V = R*W \quad (3.5)$$

Where, W is the weight of vector criteria as evaluated with AHP and $V = [v_{ij}]_{m\times n;}$ i = 1, 2, m; j = 1, 2, n

Step 5: Generate the ideal and negative-ideal solution for the critical success factors using Equation 3.6 (Singh and Agrawal 2018).

$$A^+ = \{V_{w1}^*, V_{w2}^* \ldots\ldots\ldots\ldots V_{wn}^*\} \text{ and } A^- = \{V_{w1}^-, V_{w2}^- \ldots\ldots\ldots\ldots Vwn^-\} \quad (3.6)$$

The values as per Equation 3.7 are considered for the ideal positive and ideal negative solutions.

$$V^* = (1, 1, 1) \quad \text{and } V^- = (0, 0, 0) \quad (3.7)$$

Step 6 Compute the total distances from fuzzy positive ideal solution (FPIS) and fuzzy negative ideal solution (FNIS) for each factor using Equation 3.8 (Singh and Agrawal 2018).

$$D^{+} = \frac{\sum_{i=1}^{m} d\left(V - V^{*}\right)}{m} \qquad (3.8)$$

$d\left(V - V^{*}\right)$ is the distance between two fuzzy numbers, which is determined using Equation 3.9

The $d(V_1 - V_2) = \sqrt{\frac{1}{3}[(g_2 - g_1)^2 + (h_2 - h_1)^2 + (i_2 - i_1)^2]}$ (3.9)

Along similar lines, the distance from the negative ideal solution is evaluated using Equation 3.10

$$D^{-} = \frac{\sum_{i=1}^{m} d\left(v - v^{-}\right)}{m} \qquad (3.10)$$

Step 7: Compute the relative closeness to the ideal solution using Equation 3.11

$$C = D^{-} / (D^{+} + D^{-}) \qquad (3.11)$$

Step 8: Rank the critical Success factors based on the order of the values of C.

3.6 Decision-Making Trial and Evaluation Laboratory

In multi-criteria decision situations, DEMATEL method was used to assess direct and indirect influences among factors (Gandhi et al., 2015). DEMATEL was used to analyze cloud adoption drivers and prioritize investment project portfolios and agri-food supply chains for sustainable initiatives (Hidayanto et al., 2015; Altuntas and Dereli, 2015; Mangla et al., 2018). This approach was also used to assess the enablers and green supply chain management techniques in solar power advancements (Lin, 2013; Luthra et al., 2016). Singh et al. (2019) have used DEMATEL to analyze the ICT application in SMEs in the food industry. The step-by-step procedure of the DEMATEL approach is detailed in the following subsection.

3.6.1 Procedure of the DEMATEL Approach

The main steps for applying the DEMATEL approach are as follows:

Step 1: Collect expert responses and evaluate their average to obtain the average matrix Z.

Consider ‘m’ experts and ‘n’ factors for the analysis. Expert opinion is based on pair-wise comparison to get the direct influence between two factors. x_{ij} denotes the degree of influence of factor i on j as per expert view. The integer scores of 0, 1, 2, 3, and 4 denote no influence, low influence, medium influence, high influence, and very high influence, respectively. An *n x n* non-negative matrix, $X^k = [x_{ij}^k]$ is obtained from each expert. The average matrix Z= [*zij*] is obtained per Equation 3.12 and represents the aggregate of all responses.

$$z_{ij} = \frac{1}{m}\sum_{i=1}^{m} x_{ij}^{k} \quad (3.12)$$

Step 2: Generate the normalized initial direct-relation matrix, N

The matrix, N= [nij], where the value of each element in matrix N ranged between [0, 1], is evaluated using Equation 3.13.

$$N = \lambda * Z, \text{ or } [n_{ij}]_{nxn} = \lambda\, [z_{ij}]_{nxn} \quad (3.13)$$

$$\text{Where } \lambda = \text{Min}\left[\frac{1}{\max 1 \le i \le n \sum_{j=1}^{m} |Z_{ij}|}, \frac{1}{\max 1 \le i \le n \sum_{j=1}^{n} |Z_{ij}|}\right]$$

Step 3: Develop the total relation matrix Y.

Total relation matrix Y is derived using Equation 3.14, and its individual element represents the indirect effect of factor i on factor j. Matrix Y shows the total relationship between each pair of critical Success factors.

$$Y = N(I-N)^{-1} \quad (3.14)$$

Where I is the Identity matrix.

Step 4: Determine the sums of rows and columns of the Total relation matrix Y

The sums of rows and columns of matrix Y are denoted by vectors S_R and S_C, which are evaluated using Equation 3.15.

$$S_R = [r_i]_{nx1} = \left(\sum_{j=1}^{n} y_{ij}\right)_{nx1} \text{ and } S_C = [c_j]_{1xn} = \left(\sum_{j=1}^{n} y_{ij}\right)'_{1xn} \quad (3.15)$$

The S_R and S_C indicate that the total sum given, and total sum received have an impact on factor i's influence on the other factors both directly and indirectly.

Step 5: Develop a cause-and-effect relationship

The cause-and-effect diagram is constructed in a coordinate plane using the values of $S_R + S_C$ and $S_R - S_C$ as abscissa and ordinate, respectively. Interrelationships among system factors are established using the cause-and-effect diagram. Critical success factors are classified into the cause-and-effect group based on the values of (SR - SC). If the score of ($S_R - S_C$) is positive, critical Success factors fall in the cause group and directly affect other critical Success factors. On the other hand, if the score of ($S_R - S_C$), is negative, such critical Success factors belong to the effect group, and the other critical success factors influence these.

3.7 Empirical Analysis

A survey method is used to validate the proposed conceptual framework for adopting BDA in the context of Indian Manufacturing. The empirical analysis is a commonly used method by researchers for checking and validating the proposed model. Survey method depends on facts collected from literature and experience and then allow the data collection through structured questionnaire. The collected data is examined and analyzed to interpret and validity the results for proposed framework. The main steps for performing empirical analysis are as follows:

Step 1: Domain specialists were consulted in the development of a questionnaire used to compile the information. In Part A, contains the respondent's demographic and organizational details. In Part B, contains survey questions. Each concept in the questionnaire comprised three to four questions. For content validity and applicability, the preliminary questionnaire was reviewed by specialists in the respective fields. The questionnaire has been reviewed by specialists who have made a few changes to make it more applicable to current research. Measures on a 7-point Likert scale were used to evaluate all of the reflective markers (i.e., strongly disagree to strongly agree). Please refer to Appendix 10 for the final survey.

Step 2: The information was gathered from people who have works in the Indian manufacturing industry. The information was gathered through traditional and digital means. Those questionnaires sent out to people in person, or “offline.” A Google form link was developed to facilitate the online submission of questionnaires and to reach the largest possible audience. We emailed them and requested them to fill out the survey. About 1050 Indian professionals in their respective fields were polled for this study. In total, 305 out of 1050 queries were answered. Participants were representatives of Indian factories.

Step 3: We used empirical methods to assess the questionnaire data we gathered. The suggested conceptual framework has been subjected to tests to ensure the validity and reliability of the data used in it. A smart PLS software is also used to create the structural model. The first step of the inquiry is to create a metric that accounts for every variable of interest. After conducting the data analysis, this step introduced the empirical results and research findings after thorough discussions and using SPSS version 25.0 (IBM, 2017) for Exploratory Factor Analysis and the Smart PLS tool for Confirmatory Factor Analysis and Structured Equation Modelling.

3.8 Summary of Chapter

This chapter thoroughly discussed the research methodology used in this research work. The chapter begins with the research questions for the research work, based on the research objective mentioned in chapter 2. This chapter presented a detailed justification of different multicriteria decision-making approaches used in this study. A graphical representation of the research methodology has been provided. Barriers to BDA implementation in manufacturing are discussed in the next chapter, along with an analysis of those barriers using multi-criteria decision-making techniques.

CHAPTER 4

ANALYSIS OF BARRIERS TO BIG DATA ANALYTICS IMPLEMENTATION

This chapter provides a detailed analysis of barriers to big data analytics implementation. The structure of this chapter is as follows: “Introduction” section provides introduction of this chapter. In “Statistical Analysis of Barriers” section, the statistical data analysis in terms of descriptive analysis is discussed. “Modeling of Barriers using Graph Theory Matrix Analysis” section deals with modeling of barriers using GTMA. Finally, the summary of this chapter is provided in "Chapter Summary" section.

4.1 Introduction

In the current business environment of Industry 4.0 and circular economy, organizations are taking the help of emerging technologies for proper decision-making and sustainable manufacturing operations. Big data analytics has emerged as an important tool for right decision-making by using a high volume of unstructured data from different sources. Although BDA is emerging as a source of competitive advantage for organizations, making a big investment in BDA is challenging. This chapter deals with the identification, prioritization, several groups of barriers to the investment of big data analytics. Descriptive analysis was carried out using factor analysis for prioritization, and the evaluation of barriers intensity was done using the Graph theory matrix approach.

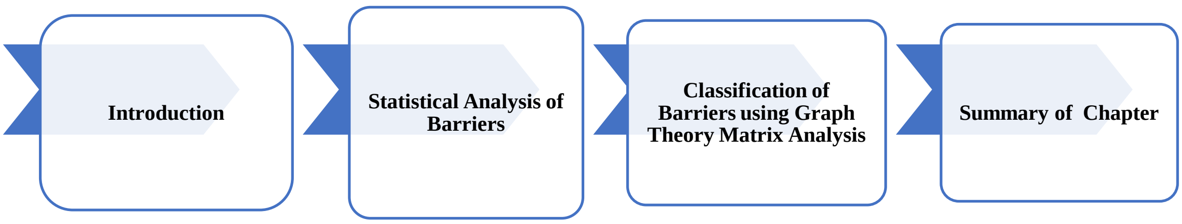

Figure 4.1 Chapter Flow Diagram

Chapter 2 identified important barriers to BDA adoption in the manufacturing industry based on a literature review. The following Figure 4.1 illustrates the chapter's flow.

4.2 Statistical Analysis of Barriers

The following section discusses the descriptive analysis for selecting the critical barriers and exploratory analysis for categorizing the barriers.

- ***Data* collection:**

A questionnaire was developed in consultation with domain experts for data collection. The expert's responses on the impact of barriers on investment in BDA for Indian manufacturing sector organizations were gathered on a five-point Likert scale (i.e., 1- Very low, 2- Low, 3- Medium, 4- High, 5- Very high). Overall, 201 responses were collected from manufacturing firms. The respondents' demographic details under the categories of Respondent profile, Type of industry, Experience, and Number of employees are shown in Table 4.1. General managers, managers, assistant managers, and others fall in the respondent's profile category. The industries selected for data collection include automobile, metal and machinery, sheet metal, and other industries. Under the experience category, the respondents were grouped in the experience of 0 to 5, 6 to 10, 11-15, 16-20, and more than 20 years. The last category of respondents is related to the number of employees in the industry (i.e., <100 to >500).

Table 4.1 Demographics Details of Respondents

Categories	Demographic detail	Number of Respondents	Percentage of Respondent
Respondents profile	General Managers	36	17.91
	Managers	47	23.38
	Assistant Managers	75	37.32
	Others	43	21.39
	Total	201	100
Type of Industry	Automobile	85	42.29
	Metal and Machinery	25	12.43
	Steel Industry	54	26.86
	Others	37	18.42
	Total	201	100
Experience (In Years)	>20	58	28.85
	16-20	62	30.84
	11-15	48	23.89
	6-10	21	10.45

	0-5	12	5.97
	Total	201	100
Number of employees	>500	77	38.31
	251-500	39	19.41
	101-250	53	26.36
	<100	32	15.92
	Total	201	100

Respondents with 16–20 years of experience, those working in the automobile industry, and those employed by companies with more than 500 workers accounted for the bulk of the data. Other respondent profiles, those with less than five years of experience, and businesses with fewer than one hundred employees had the lowest response rates.

- ***Data validation/ reliability testing:***

The data validation check is performed using a correlation test named Bartlett's test of sphericity. It is performed to check the homogeneity of the data. A value of less than 0.05 of the significance level indicates that the available data is appropriate for the factor analysis. The reliability test is conducted for the internal consistency of the data. A reliability measure known as Cronbach's Alpha is calculated for this purpose. The value of Cronbach's Alpha less than 0.7 is considered a good reliability indicator (Singh & Kumar, 2020). Further, the KMO analysis is done to check the sampling adequacy. KMO value should be greater than 0.6, for adequate sampling. These tests can easily be done by statistical software such as SPSS and Minitab.

- ***Descriptive analysis:***

Descriptive analysis of the barriers is based on descriptive measures (mean and standard deviation). Based on the mean value, ranking for the BDA barriers is done, and the most important barriers are identified. Descriptive factor analysis can be performed using statistical software such as SPSS Version 25.0 (IBM, 2017).

4.2.1 Findings of Statistical analysis

This section presents the findings of statistical analysis of data obtained from respondents, and factor analysis is applied to factorize the seventeen identified BDA barriers into organizational, data management, and human barriers. The data was collected from 201 respondents for this analysis. The reliability test was conducted to check the data's internal consistency using statistical software – SPSS Version 25.0. The value of Cronbach's α was found to be 0.869, which is a good indicator of reliability, i.e., more than 0.7. Further, Bartlett's test was conducted, and it was found that P-value was less than 0.05. If the determinant of the correlation matrix is greater than 0.00001, then there is no multicollinearity. The KMO value obtained is 0.882, which is higher than 0.6, which shows that the sampling is a good indicator of the consistency of the barriers. These statistical tests established that the data was suitable for factor analysis. On the basis of pareto analysis seventeen barriers were finalized (Refer Figure 4.2).

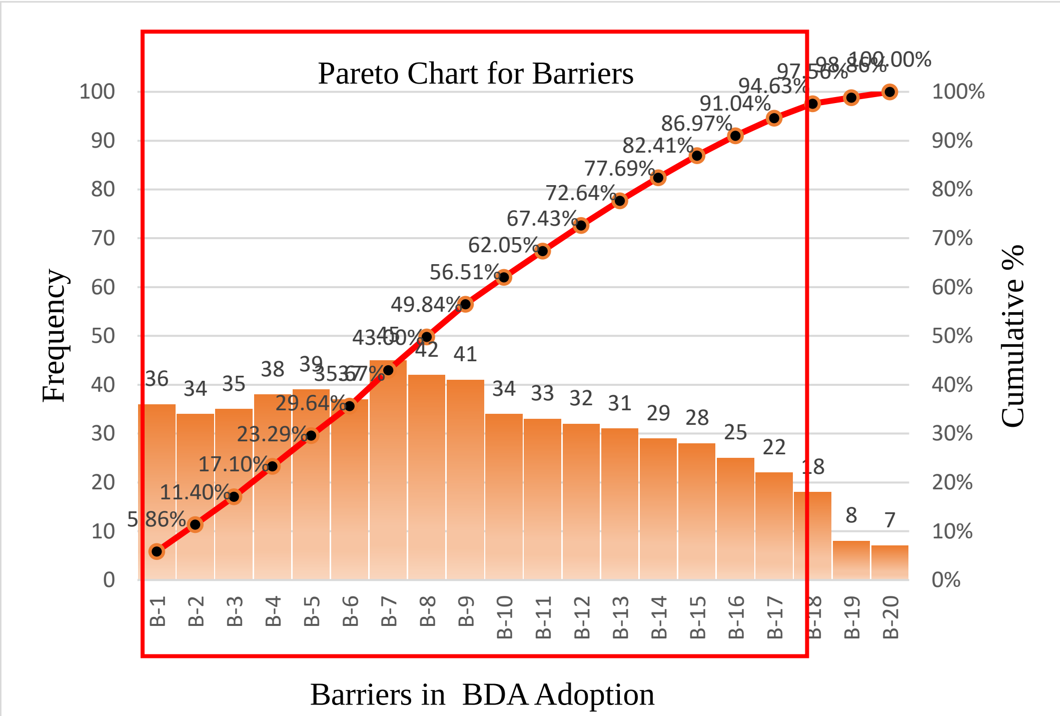

Figure 4.2 Pareto Analysis of Barriers in BDA Adoption

Additionally, mean and standard deviation were the primary statistical tools used in the barrier descriptive analysis. The means of the 17 barriers were used to determine an order of importance (Refer, Table 4.2). The absence of staff buy-in for new tech deployments was the biggest deterrent to BDA investment (Mean = 4.1642). The next most important barrier is the high price of hiring skilled BDA consultants (Mean = 3.8856), followed by the high price of integrating data across the supply chain (Mean = 4.0746), the high price of training programmes on BDA (Mean = 3.9403), the lack of trust and commitment among employees (Mean = 3.9204), and the inadequate data sharing policy among stakeholders (Mean = 3.8905). Investing in BDA technology was hampered by a few minor factors, including a lack of data security and privacy regulations and a lack of research on uses of BDA tools (Mean =3.5423 and 3.5920, respectively).

Table 4.2 Descriptive Analysis of the Barriers to Investment in BDA

Barriers	Mean	Std. Deviation	Ranking
B-1	3.5423	1.28041	17
B-2	3.6020	1.17507	15
B-3	3.6517	1.22805	12
B-4	3.6567	1.17753	11
B-5	3.8060	1.21539	8
B-6	3.7463	1.09558	9
B-7	3.5920	1.11926	16
B-8	3.7214	1.04498	10
B-9	3.6368	1.17151	14
B-10	4.1642	1.01386	1
B-11	3.6468	1.18305	13
B-12	4.0746	1.02927	2
B-13	3.8856	1.23363	6
B-14	3.9403	1.11194	3
B-15	3.8905	1.10361	5
B-16	3.9204	1.08795	4
B-17	3.8061	1.12123	7

Three categories of barriers are formulated based on eigenvalues greater than 1 obtained in factors analysis. These categories include organizational barriers, data management, and human barriers in consultation with domain experts (Refer to Table 4.3). The organization's seven barriers explained 22.617% of the variance. The principal component analysis was used as an extraction method for segregating the barriers. Varimax with Kaiser normalization (Cutoff = 0.50) was used as a rotation method. Finally, three components are taken after rotation of the component matrix with Varimax. These barriers are segregated into a particular category based on their factor loading. The seven barriers extracted for the organization barriers category were Lack of policies for data security and privacy (77.10%), High cost of developing digital Infrastructure (68.70%), Absence of data-driven organizational culture (66.90%), Rigid organizational culture for making new investments (65.50%), Lack of confidence of return on investment in BDA implementation (63.90%), Lack of research on applications of BDA tools (63%) and Ineffective performance framework for assessing effectiveness (61.80%).

Table 4.3 Factor Analysis for categorization of Barriers to Investment in BDA

Categories of barriers	Barriers	Factor Loading	Eigen Value
Organizational Barriers	B-1	0.771	5.625
	B-2	0.687	
	B-3	0.669	
	B-4	0.655	
	B-5	0.639	
	B-6	0.630	
	B-7	0.618	
	B-8	0.62	

Data Management Barriers	B-9	0.617	1.367
	B-10	0.615	
	B-11	0.58	
	B-12	0.517	
	B-13	0.501	
Human Barriers	B-14	0.700	1.255
	B-15	0.641	
	B-16	0.588	
	B-17	0.568	

This category accounted for 33.088% of the variance (Refer to Table 4.4). It also claim that the awareness level of BDA among the manufacturing industry is moderate for most of the survey respondents. Verma and Bhattacharyya (2017) found that proper technology infrastructures, organizational culture, and architecture standards should be developed for a successful investment in BDA. Beath et al. (2012) found that the main cause of the high percentage of BDA implementation failure is the lack of a data-driven culture within enterprises.

Lack of competence for using BDA in resource optimization (62%), absence of coordination among stakeholders for BDA-related activities (61.70%), lack of availability of specific BDA tools as per industry requirements (61.50%), inadequate data sharing policy among stakeholders (58%) high cost associated with integrating data across the supply chain (51.70%) and high costs associated with managing unstructured data (58%) were the six barriers extracted for the data management barriers category. All of the factor loadings are denoted by the numbers in the brackets. 9.044% of the total variation may be attributed to this factor.. Nwankpa and Roumani (2014) noted that senior management's provision of support and resources for the introduction of new technologies makes data management a crucial barrier category. Baldwin (2015) stated that 66% of businesses saw poor results from their data management efforts. Therefore, the manufacturing industry must give due thought to data management.

The four barriers extracted for the human barriers category were the High cost of training programs on BDA (70%), lack of support from employees for implementing modern technologies (64.10%), Lack of trust and commitment among employees (58.80%), and High cost of hiring skilled BDA consultants (56.80%). This category accounted for 8.385% of the variance. Alalawneh and Alkhatib (2021) stated that companies ought to offer BDA-investment-friendly training courses, funds, facilities, and advisory services. The following subsection builds digraphs for each type of obstruction using Analysis of Matrices in Graph Theory.

Table 4.4 Total Variance Explained (extraction method) Principal Component Analysis

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Eigenvalues	% of Variance	Cumulative %	Eigenvalues	% of Variance	Cumulative %	Eigenvalues	% of Variance	Cumulative %
1	5.625	33.088	33.088	5.625	33.088	33.088	3.845	22.617	22.617
2	1.367	9.044	42.132	1.367	9.044	42.132	2.580	16.178	38.795
3	1.255	8.385	50.517	1.255	8.385	50.517	1.823	11.722	50.517
4	0.990	5.826	54.343						
5	0.932	5.481	59.825						
6	0.848	4.990	64.815						
7	0.796	4.682	69.497						
8	0.771	4.537	74.034						
9	0.683	4.015	78.050						
10	0.610	3.589	81.638						
11	0.551	3.239	84.878						

12	0.532	3.132	88.010						
13	0.501	2.948	90.958						
14	0.429	2.526	93.484						
15	0.418	2.457	95.941						
16	0.375	2.206	98.147						
17	0.315	1.853	100.000						
Extraction Method: Principal Component Analysis.									

4.3 Modeling of Barriers using Graph Theory Matrix Analysis

Initially, a digraph is constructed in GTMA. A digraph is a directed graph that contains vertices and edges. The digraph is converted into a matrix form. The permanent function of the matrix is computed similarly to its determinant. To avoid any loss of information, change overall negative signs to positive signs while doing determinant calculations (Grover et al., 2006). The permanent function value is the intensity index for this study.

In this study, three categories of barriers are identified using factor analysis. These are Organization barriers (OB), Data management barriers (DMB), and Human barriers (HB). A digraph among these three categories of barriers is shown in Figure 4.3.

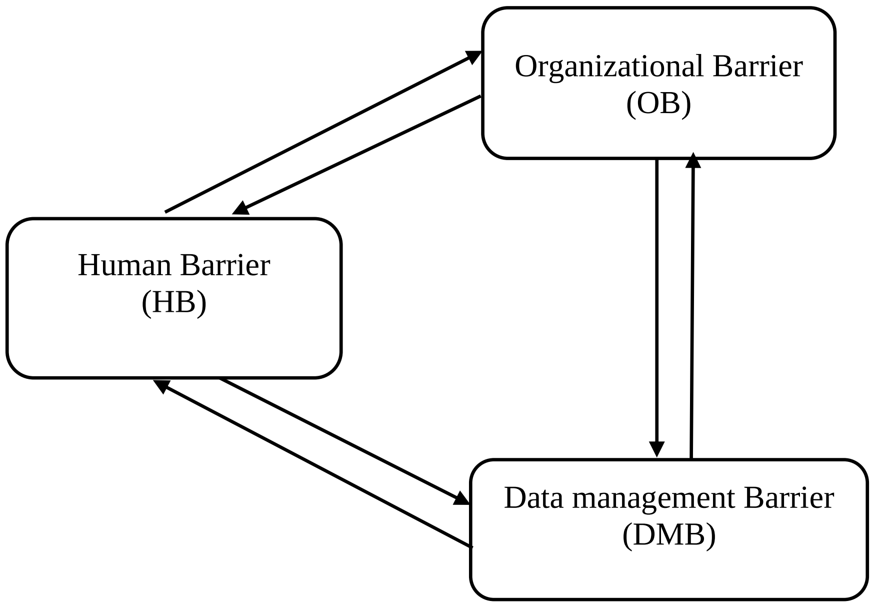

Figure 4.3 Digraph of Different Categories of Barriers (Source: Self)

This digraph is converted into matrix 'A' (Refer Equation 4.1). In the digraph, Bi's are the category of barriers represented by nodes while r_{ij}'s represent dependence through its edge. A particular value, r_{ij}, represents the degree of dependence of the j^{th} barrier category on the i^{th} barrier category. A directed edge from node i to node j represents r_{ij} in the digraph. For a digraph with n number of nodes (category of barriers), an n×n matrix [A] is obtained. The permanent function of the digraph is represented as follows:

$$|A| = \begin{vmatrix} B_1 & r_{12} & r_{13} & \cdots\cdots & r_{1n} \\ r_{21} & B_2 & r_{23} & \cdots\cdots & r_{2n} \\ r_{ij} & r_{ik} & B_i & \cdots\cdots & r_{in} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \vdots & \vdots & \vdots & & \vdots \\ r_{n1} & r_{n2} & r_{n3} & \cdots\cdots & B_n \end{vmatrix} \tag{4.1}$$

In matrix A, elements B_i and r_{ij} are the absolute and relative values, respectively. The permanent function (per) is evaluated for index value (Gupta et al., 2017).

Similarly, digraphs for an individual category of barriers are constructed. For example, as there are seven barriers in the first category, i.e., organizational barriers, the nodes $B_1^1, B_2^1, B_3^1, B_4^1, B_5^1, B_6^1, and\ B_7^1$ are used for the barriers in the first category, and r_{ij}'s symbolizes the interrelationship between them in the construction of subsystem digraph. A digraph for the organization barrier representing the relationship of one node with all the other nodes is shown in Figure 4.4.

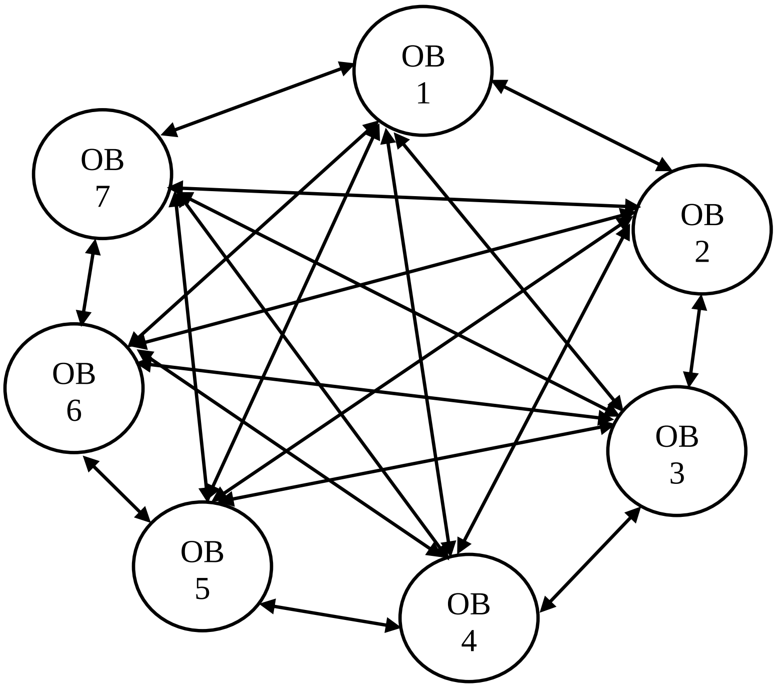

Figure 4.4 Digraph for Organization Barrier Category (Source: Self)

As seven barriers are in the organization barrier category, the digraph with seven nodes is converted into a 7×7 matrix. The permanent function, Per (B1) for the digraph (Figure 4.4), is represented as follows:

$$\text{Per}\left(\text{B1}\right) = \text{Per}\left(\text{OB}\right) = \begin{vmatrix} B_1^1 & r_{12}^1 & r_{13}^1 & r_{14}^1 & r_{15}^1 & r_{16}^1 & r_{17}^1 \\ r_{21}^1 & B_2^1 & r_{23}^1 & r_{24}^1 & r_{25}^1 & r_{26}^1 & r_{27}^1 \\ r_{31}^1 & r_{32}^1 & B_3^1 & r_{34}^1 & r_{35}^1 & r_{36}^1 & r_{37}^1 \\ r_{41}^1 & r_{42}^1 & r_{43}^1 & B_4^1 & r_{45}^1 & r_{46}^1 & r_{47}^1 \\ r_{51}^1 & r_{52}^1 & r_{53}^1 & r_{54}^1 & B_5^1 & r_{56}^1 & r_{57}^1 \\ r_{61}^1 & r_{62}^1 & r_{63}^1 & r_{64}^1 & r_{65}^1 & B_6^1 & r_{67}^1 \\ r_{71}^1 & r_{72}^1 & r_{73}^1 & r_{74}^1 & r_{75}^1 & r_{76}^1 & B_7^1 \end{vmatrix}$$

Where, $B_1^1, B_2^1, B_3^1, B_4^1, B_5^1, B_6^1, B_7^1$ represents OB1, OB2, OB3, OB4, OB5, OB6, and OB7 (sub barriers)

Manufacturing industries face obstacles in handling data due to the complexity of data. Data management barriers refer to acquire, store, protect, and process of a high volume of data and transforming them into useful information. A digraph for the data management barrier indicating the relationship of one node with all the other nodes is shown in Figure 4.5.

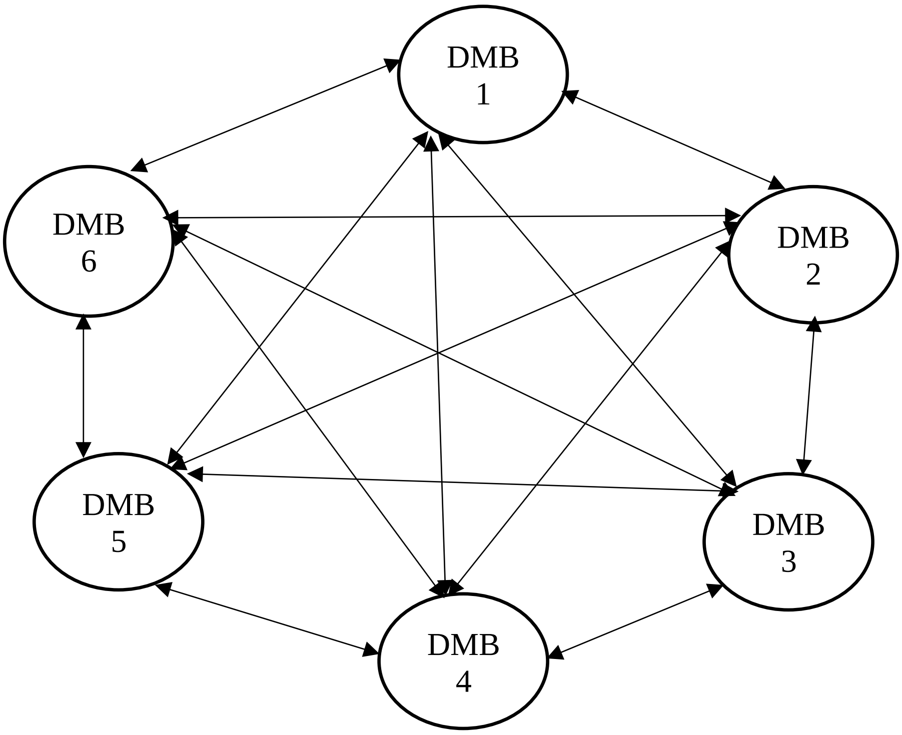

Figure 4.5 Digraph for Data Management Barrier Category (Source: Self)

The data management category includes six barriers; the digraph with six nodes is converted into a 6X6 matrix. The permanent function, per (B2 for the digraph (Figure 4.5), is represented as follows:

$$\text{Per}\left(\text{B2}\right) = \text{Per}\left(\text{DMB}\right) = \begin{vmatrix} B_1^1 & r_{12}^1 & r_{13}^1 & r_{14}^1 & r_{15}^1 & r_{16}^1 \\ r_{21}^1 & B_2^1 & r_{23}^1 & r_{24}^1 & r_{25}^1 & r_{26}^1 \\ r_{31}^1 & r_{32}^1 & B_3^1 & r_{34}^1 & r_{35}^1 & r_{36}^1 \\ r_{41}^1 & r_{42}^1 & r_{43}^1 & B_4^1 & r_{45}^1 & r_{46}^1 \\ r_{51}^1 & r_{52}^1 & r_{53}^1 & r_{54}^1 & B_5^1 & r_{56}^1 \\ r_{61}^1 & r_{62}^1 & r_{63}^1 & r_{64}^1 & r_{65}^1 & B_6^1 \end{vmatrix}$$

Where, $B_1^1, B_2^1, B_3^1, B_4^1, B_5^1, B_6^1$ represents DMB1, DMB2, DMB3, DMB4, DMB5, and DMB6 (sub barriers).

Human barriers affect the organization's ability to use BDA because of insufficient knowledge and training in this area. This barrier comprises the high cost of training programmes on BDA, lack of employee support for deploying new technology, lack of trust and commitment among employees, and high cost of recruiting skilled BDA consultants.

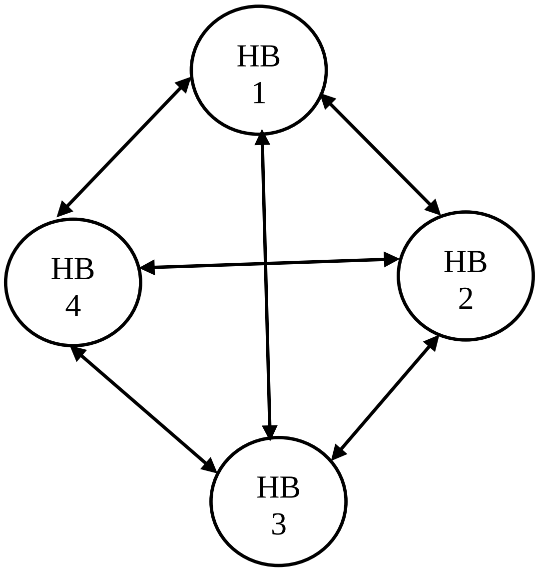

Figure 4.6 Digraph for Human Barrier Category (Source: Self)

A digraph for the organization barrier indicating the connection of one node with all the other nodes is shown in Figure 4.6. The digraph with four nodes is converted into a 4×4 matrix because there are four barriers in the human barriers category. The permanent function, Per (B3) for the digraph (Figure 4.6), is represented as follows:

$$\text{Per}\ (\text{B3})\ =\ \text{Per}\ (\text{HB}) = \begin{vmatrix} B_1^1 & r_{12}^1 & r_{13}^1 & r_{14}^1 \\ r_{21}^1 & B_2^1 & r_{23}^1 & r_{24}^1 \\ r_{31}^1 & r_{32}^1 & B_3^1 & r_{34}^1 \\ r_{41}^1 & r_{42}^1 & r_{43}^1 & B_4^1 \end{vmatrix}$$

Where, $B_1^1, B_2^1, B_3^1, B_4^1$ represents HB1, HB2, HB3, and HB4 (sub barriers).

This method will be used to find the permanent index value for each category of barriers. The higher the value of the permanent function, the more the intensity of barriers to investment in BDA.

4.3.1 Evaluation of Barriers Intensity Index

The example of passenger-car manufacturer ABC Limited has been used to illustrate the proposed approach to measuring obstacles intensity in the investment of BDA. The headquarters of the company can be found in the Delhi NCR. In order to keep up with customer demands, the corporation must invest in technological advancements. To keep the firm afloat and grow it, it is crucial to embrace novel approaches to production and design. It is a current goal of ABC Limited to cut vehicle CO2 emissions by 30%. The sector is eager for capital investment in BDA and cutting-edge manufacturing technology to guarantee eco-friendly operations. With the aid of factor analysis, we are able to single out the barriers and classify them into one of three broad classes. The challenges to implementing BDA were then quantified using a graph theory matrix. Here, we assess the intensity index for each type of barrier using the GTMA method. In order to overcome these obstacles, we divided them into three groups: human, data, and organisational. On a scale from 1 to 10, permanent matrices describing these types of obstructions are built. (1 for very low and 10 for very high) using $r_{ji} = 10 - r_{ij}$. To evaluate the permanent matrix index of organizational barriers, required inputs received from experts for absolute and relative values of barriers are:

$B^1_1 = 3$, $B^1_2 = 3$, $B^1_3 = 3$, $B^1_4 = 4$, $B^1_5 = 4$, $B^1_6 = 5$, $B^1_7 = 4$. $r^1_{12} = 3$ $r^1_{13} = 2$ $r^1_{14} = 4$, $r^1_{15} = 5$, $r^1_{16} = 2$ $r^1_{17} = 4$, $r^1_{21} = 7$ $r^1_{23} = 4$ $r^1_{24} = 3$ $r^1_{25} = 2$ $r^1_{26} = 2$ $r^1_{27} = 3$, $r^1_{31} = 8$ $r^1_{32} = 6$ $r^1_{34} = 5$ $r^1_{35} = 4$ $r^1_{36} = 3$ $r^1_{37} = 2$, $r^1_{41} = 6$ $r^1_{42} = 7$ $r^1_{43} = 4$ $r^1_{45} = 2$ $r^1_{46} = 4$ $r^1_{47} = 3$, $r^1_{51} = 5$ $r^1_{52} = 8$ $r^1_{53} = 6$ $r^1_{54} = 8$ $r^1_{56} = 3$ $r^1_{57} = 2$, $r^1_{61} = 8$ $r^1_{62} = 8$ $r^1_{63} = 7$ $r^1_{64} = 6$ $r^1_{65} = 7$ $r^1_{67} = 4$, $r^1_{71} = 6$ $r^1_{72} = 7$ $r^1_{73} = 8$ $r^1_{74} = 7$ $r^1_{75} = 8$ $r^1_{76} = 6$.

The permanent matrix of organizational barriers (OB) is calculated as follows.

$$Per(OB) = \begin{vmatrix} 3 & 3 & 2 & 4 & 5 & 2 & 4 \\ 7 & 3 & 4 & 3 & 2 & 2 & 3 \\ 8 & 6 & 3 & 5 & 4 & 3 & 2 \\ 6 & 7 & 5 & 4 & 2 & 4 & 3 \\ 5 & 8 & 6 & 8 & 4 & 3 & 2 \\ 8 & 8 & 7 & 6 & 7 & 5 & 4 \\ 6 & 7 & 8 & 7 & 8 & 6 & 4 \end{vmatrix} = 210684578$$

Similarly, values of permanent data management barriers and human barriers are calculated as:

$$Per(DMB) = \begin{vmatrix} 5 & 3 & 4 & 3 & 3 & 2 \\ 7 & 4 & 2 & 3 & 3 & 2 \\ 6 & 8 & 5 & 2 & 3 & 4 \\ 7 & 7 & 8 & 3 & 4 & 3 \\ 7 & 7 & 7 & 6 & 3 & 4 \\ 8 & 8 & 6 & 7 & 6 & 4 \end{vmatrix} =6264473$$

$$Per(HB) = \begin{vmatrix} 9 & 7 & 8 & 7 \\ 3 & 7 & 9 & 7 \\ 2 & 1 & 8 & 8 \\ 3 & 3 & 2 & 9 \end{vmatrix} = 21854$$

The values for permanent data management and human barriers are 6264473 and 21854, respectively.

Along similar lines, the overall barrier index value is evaluated. The overall barriers intensity (OBI) for investment in BDA is computed as:

$$\text{Per(OBI)} = \begin{vmatrix} 21854 & 6 & 5 \\ 4 & 6264473 & 7 \\ 5 & 3 & 210684578 \end{vmatrix} = 3.86 \text{ x } 10^{17}$$

The degree to which a given group of obstacles affects BDA investment prospects is proportional to the index value assigned to that group. The greater the index value, the more severe the constraints are on BDA investment. It was shown that the intensity of organisational barriers is highest (210684578), while the intensity of personal barriers is lowest (21854). The results are similar to other findings in the literature. Gunasekaran and Spalanzani (2012) concluded that organizations play a significant role in implementing BDA and modern technologies for sustainable activities. Organizations should motivate employees to work for the goal of sustainable operations and inculcate business ethics (Govindarajulu & Daily, 2004). More focus should be placed on removing the organisational barriers, followed by the data management and human barriers. Top management should have prepared to verify its implementation to lessen the impact of these obstacles. Organizational performance, environmental impact, and resource use are all positively impacted by technologies like BDA and I4.0. (Saleem et al., 2020). Organizations should develop capabilities for implementing BDA to meet the requirements of sustainable operations (Vargas et al., 2018). Many organizations focus on short-term goals, ignoring the implementation of modern technologies such as BDA, industry 4.0, etc., due to the fear of heavy investment and risks of failure. Organizational culture also plays a crucial role in motivating employees to adopt the organization’s changes. In terms of organizational barriers, there is an apparent consensus among experts (65.22%) about the importance of this category for the manufacturing sector (Alalawneh & Alkhatib, 2021).

The data management barrier category has the second highest index (6264473) value and influences investment in BDA. Further, organizations adopt emerging technologies in their manufacturing operations and manage the increasing data flow in their value chain for effective management (Ghadge et al., 2020). Organizations should be flexible in adopting modern technologies. Therefore, organizations need to comprehend the significance of modern technologies and overcome different barriers to investment in modern technologies.

4.4 Summary of Chapter

In this chapter, an analysis of barriers has been done. The factor analysis has been applied to categorize all barriers into different groups. Further, graph theory and matrix approach has been employed to evaluate the intensity of barrier classes. From the literature and experts' opinion, 17 barriers have been selected. Based on factor loading, the barriers are grouped into three categories, i.e., organization, data management, and human. These categories are prioritized based on the value of the index. A high index value depicts the higher intensity of barriers, whereas a low-value index signifies the lesser intensity of barriers in BDA implementation.

The chapter's findings will significantly motivate organizations to invest in BDA applications in manufacturing organizations. This research may also help manufacturing organizations develop strategies for making an effective investment for BDA implementation. In the next chapter, the modeling of critical success factors for BDA implementation will be discussed and analyzed using different multi-criteria decision-making approaches.

CHAPTER 5

MODELING OF CRITICAL SUCCESS FACTORS FOR BIG DATA ANALYTICS IMPLEMENTATION

In this section, we model the most important considerations for achieving success with big data analytics. This section is organised as follows: The chapter's introduction can be found in the "Introduction" section. Justification of BDA Application is presented in the "Justification of BDA Application" section. In the section titled "Ranking of Critical Success Factors for the Application of BDA by Fuzzy TOPSIS," the subject of ranking CSFs for the application of BDA is discussed. Using the DEMATEL framework, "Categorization of Critical Success Factors in terms of Cause and Effect" provides the categorization of CSFs in terms of their causal relationships with one another. The "Chapter Summary" section provides a short overview of this chapter.

5.1 Introduction

This chapter provides an argument for the use of big data analytics in the Indian manufacturing sector. Some of the many advantages of BDA are discussed in Section 2.1 of Chapter 2. In addition to its primary aim of attaining organizational targets, the manufacturing industry may also focus on operational performance by incorporating modern technology into manufacturing processes.

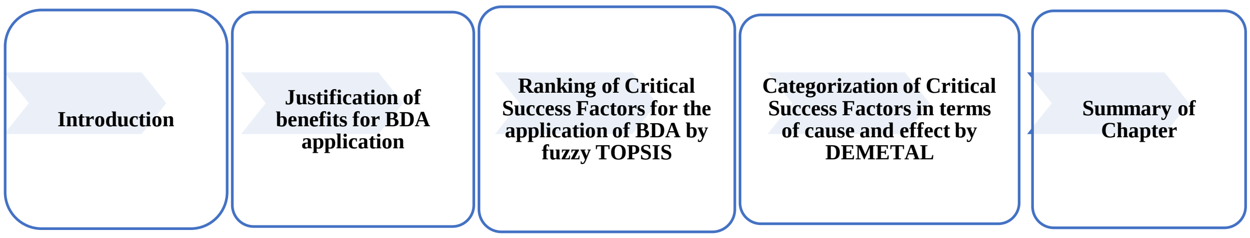

Figure 5.1 Chapter Flow Diagram

The argument for evaluating the advantages of big data analytics in the Indian Manufacturing Industry is presented in this chapter. In Figure 5.1, the chapter flow is shown. The benefits and critical success factors for BDA implementation in the manufacturing industry were identified as summarized in chapter 2. The AHP method is applied for the justification of the BDA benefits. The Fuzzy TOPSIS approach is employed for ranking critical success factors, and the DEMATEL tool is used to analyze the cause and effect of critical success factors.

5.2 Justification of BDA Application

This section evaluates the priority vector relative weights for the BDA benefits identified and the global desirability index (GDI) for two alternatives. The first alternative is big data-enabled manufacturing (BDM), and the second is without big data-enabled manufacturing (WBDM). A higher value of GDI indicates a better alternative. The justification of BDA in the manufacturing sector is analyzed based on the framework developed using AHP. Initially, a pairwise comparison matrix (P_1) for seven benefits of BDA at level 2 of the AHP model is developed, as shown in Table 5.1. Each element of this matrix signifies its relative importance and evaluated as per procedure given in section 3.4.1. For example, $p_{23} = 5$ signifies benefit in the second row (Energy efficient and safe processes) has vital importance over the benefit at the third column (Improved customer satisfaction). Element p_{32} is the reciprocal of p_{23} and interpreted accordingly as per the Saaty scale (refer to Appendix A1). The pairwise comparison results are shown in Table 5.1. Further, the priority vector is determined as per the procedure given in section 3.4.1 for all seven benefits, and it signifies the relative weight of each benefit. The priority vector is shown in the last column of Table 5.2. Additionally, the Consistency Ratio (CR) is evaluated following the procedure to examine the degree of consistency in the pairwise comparison of seven BDA benefits (Appendix A3). Normalized matrix 'N' is developed using procedure given in Section 3.4.1 and the P value is shown in Table 5.2. The evaluated value of CR is 0.0923, which is less than 0.1 Refer Appendix A 2 and A3. This signifies a good level of consistency in the relative decision about BDA benefits.

Table 5.1 Pairwise Comparison Matrix of BDA Benefits (Level 2) ‘P_1’

	EPRR	EESP	ICS	IPM	WM	RO	DSC
EPRR	1	0.143	0.25	0.2	0.2	0.33	0.12
EESP	7	1	5	3	2	6	0.33
ICS	4	0.2	1	0.33	0.2	5	0.25
IPM	5	0.33	3	1	0.33	4	0.2
WM	5	0.5	5	3	1	7	0.5
RO	3	0.167	0.2	0.25	0.14	1	0.16
DSC	8	3	4	5	2	6	1
Total	33	5.34	18.45	12.8	5.87	29.33	2.5

Enhanced production recovery and Reuse (EPRR), Energy- efficient and safe processes (EESP), Improved customer satisfaction (ICS), Improvement in profit margin (IPM), waste minimization (WM), Resources optimization (RO) and developing sustainable capabilities (DSC).

Subsequently, for each sustainability benefit, the priority vector is evaluated for both the alternatives, i.e., big data-enabled manufacturing (BDM) and without big data-enabled manufacturing (WBDM) following the similar procedure as given in Section 3.4.1.

Table 5.2 Normalized Matrix N and Priority Vector for BDA Benefits

	EPRR	EESP	ICS	IPM	WM	RO	DSC	Priority Vector (PV)
EPRR	0.03030	0.0267	0.0135	0.0156	0.0340	0.0112	0.048	0.025
EESP	0.2121	0.1872	0.2710	0.2343	0.3407	0.2045	0.132	0.2260
ICS	0.1212	0.0374	0.0542	0.0257	0.0340	0.1704	0.100	0.0765
IPM	0.1515	0.0617	0.1626	0.0781	0.0562	0.1363	0.08	0.1030
WM	0.1515	0.0936	0.2710	0.2343	0.1703	0.2386	0.200	0.1940
RO	0.0909	0.0312	0.0108	0.0195	0.0238	0.0340	0.064	0.0395
DSC	0.2424	0.5617	0.2168	0.3906	0.3407	0.2045	0.400	0.3360

The results are shown in Table 5.3. For example, for benefit EPRR, the value of PV is 0.889 and 0.111 for BDM and WBDM, respectively. All the elements of row are divided by the sum of the row here 1 is divided by 1.125 and 0.125 is divided by 1.125 then take the average of all the element in the row. A higher value of PV in the case of BDM shows that big data-enabled manufacturing is justified when Enhanced Production Recovery and Reuse, benefit was considered. It is observed from the results (Table 5.3) that in terms of all seven benefits, manufacturing organizations with BDA have more priority vector value than manufacturing organizations without BDA. On similar lines PVs were evaluated for all benefits and these results are summarized in Table 5.3. Also, CR for all pairwise comparison matrices for seven benefits were evaluated and found within the range.

Table 5.3 Pairwise Comparison Matrix and priority Vectors

Attributes	Alternative	BDM	WBDM	Total
EPRR	BDM	1	0.125	1.125
	WBDM	8	1	9
	PV	0.889	0.111	
EESP	BDM	1	0.125	1.125
	WBDM	8	1	9
	PV	0.889	0.111	
ICS	BDM	1	0.1429	1.1429
	WBDM	7	1	8
	PV	0.875	0.125	
IPM	BDM	1	0.1429	1.1429
	WBDM	7	1	8
	PV	0.875	0.125	
WM	BDM	1	0.125	1.125
	WBDM	8	1	9
	PV	0.889	0.111	
RO	BDM	1	0.1667	1.1667
	WBDM	6	1	7
	PV	0.857	0.143	
DSC	BDM	1	0.1429	1.1429
	WBDM	7	1	8
	PV	0.875	0.125	

Table 5.4 Weights of Attributes for Alternatives

Sr. No.	Attributes	Weights of Benefits (Refer Table 5.2)	Local weight of each Benefit	
			BDM	WBDM

1	EPRR	0.025	0.889	0.111
2	EESP	0.2260	0.889	0.111
3	ICS	0.0765	0.875	0.125
4	IPM	0.1030	0.875	0.125
5	WM	0.1940	0.889	0.111
6	RO	0.0395	0.875	0.143
7	DSC	0.3360	0.875	0.125

Table 5.5 summaries weights of each benefit and local weights of alternatives (BDM/WBDM) on the basis of each benefit.

Table 5.5 Desirability Index of Alternatives

Sr. No.	Attributes	Global weight of each Alternative	
		BDM	WBDM
1	EPRR	0.0223	0.0027
2	EESP	0.2009	0.0251
3	ICS	0.0669	0.0094
4	IPM	0.0901	0.0127
5	WM	0.1724	0.0214
6	RO	0.0345	0.0056
7	DSC	0.294	0.0420
Total global weight		0.8811	0.1189

Table 5.6 Global Desirability Index of Alternatives

1	Global desirability index of BDM	0.8811
2	Global desirability index of	0.1189

More specifically, we multiply the local weight of each option by its benefit weight to get the global weight for each option. The resulting alternatives' preferability indices are displayed in Table 5.5. Then, the GDI is calculated by adding the values of all viable choices. The GDI values for BDM and WBDM are 0.8811 and 0.1189, respectively, as shown in Table 5.6. A higher value of GDI justifies the benefits of BDA application.

5.3 Ranking of Critical Success Factors for the Application of BDA by Fuzzy TOPSIS

The literature is analysed to determine the critical success factors for the successful implementation of BDA in the industrial industry. Experts were consulted, and from a purely strategic standpoint, the final ranking of 15 elements was arrived at. Pareto analysis of their finalized critical success factors is displayed in Figure 5.2.

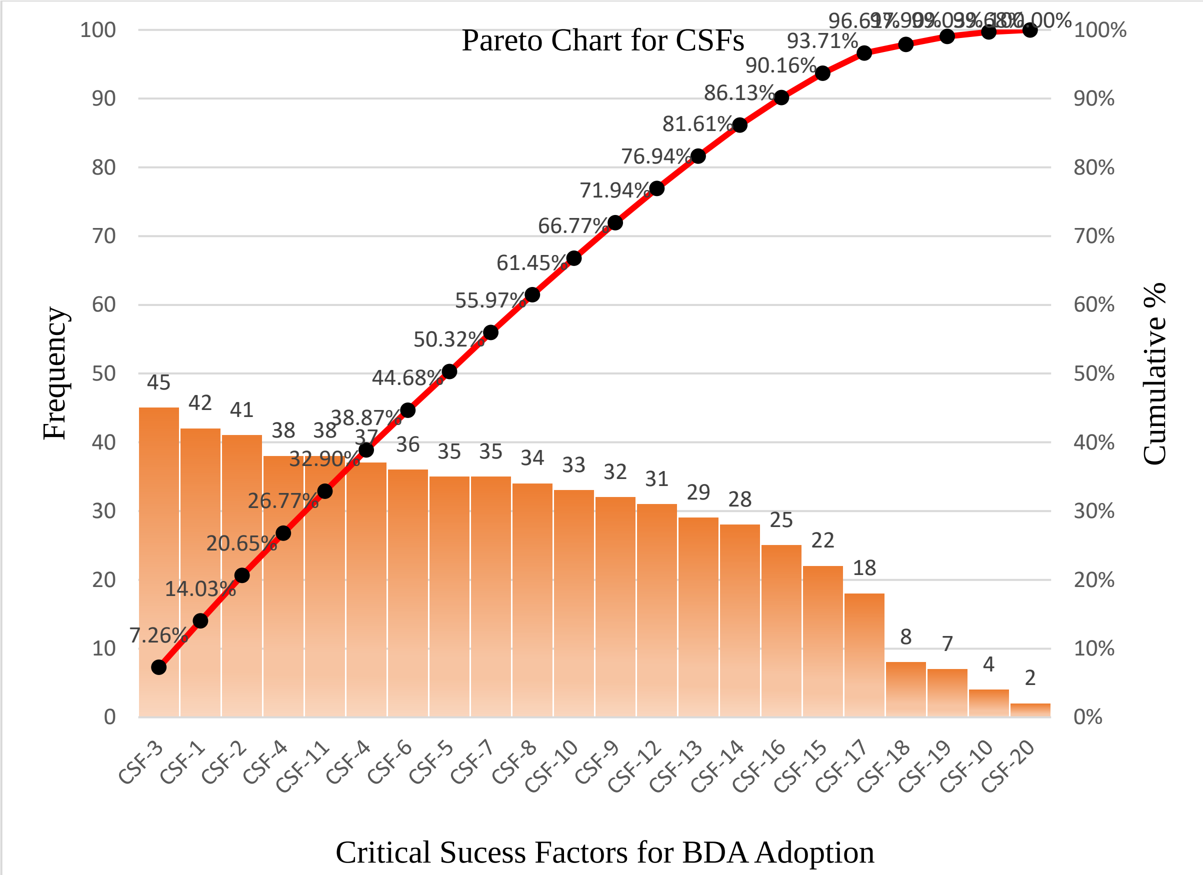

Figure 5.2 Pareto Analysis for Critical Success Factor

To further understand how BDA is being used in India's manufacturing industry, a survey based on questionnaires was undertaken. Those chosen to serve as experts came from both the private sector and the academic world. Experts were asked to fill out a survey made specifically for this investigation. Two production managers, one marketing director, an operations engineer, a logistics director, and two professors make up the expert team. The specialists in the business world have been working in their field for over 10 years, while the academic experts have been in the field for over fifteen years. All 15 critical success factors were asked to be rated in linguistic terms by a panel of seven experts. For this reason, a 5-point scale was employed, with the labels very low (VL), low (L), medium (M), high (H), and very high (VH) serving as the descriptors. With the help of a scale, the writers compiled the responses of linguistic terms of experts and translated them into crisp values by referring to scale (Table 3.1). Thus, the matrix so obtained is called fuzzy decision matrix D, and it is shown in Appendix A4. Then matrix D is converted into an un-weighted fuzzy matrix, R using Equation 3.4, and the same is given in Appendix A5. Further, the weighted normalized matrix is evaluated using Equation 3.5. This evolves the product of the unweighted fuzzy decision matrix R (Appendix A5) and the PV value for benefits in Table 5.2. The same is shown in Table 5.6.

Next, the distance of the rating of each factor from a positive ideal solution is evaluated using Equation 3.8. This is given in Appendix A6. Similarly, the length of the rating of each factor from a negative ideal solution is estimated using Equation 3.10 and shown in Appendix A7. Further, the total distance of each factor is calculated from the positive and negative ideal solution. D^+ and D^- represent these$^-$ and the same is given in Appendix A6 and A7 respectively. Subsequently, the relative closeness concerning ideal solution A^+ is evaluated using Equation 3.11, and the same is used in the performance ranking. The biggest value of closeness is ranked '1,' and the lowest value of closeness is ranked '15'. Following this closeness value, all the critical success factors are ranked and tabulated in Table 5.8. Commitment and engagement of top management, strategy development for BDA, and development of capability for handling big data are prioritized as 1st, 2nd, and 3rd in their relative importance, which is crucial for BDA implementation. Without commitment and support from top management, such high-cost initiatives cannot be successful. Management should also develop a trained workforce to manage massive data through BDA. Responsive information sharing framework and development of contract agreement among all stakeholders are ranked 14thand 15th, respectively and these factors have relatively less impact on the implementation of BDA.

5.4 Categorization of Critical Success Factors in Terms of Cause and Effect by Decision Making Trial and Evaluation Laboratory

The Decision-Making Trial and Evaluation Laboratory (DEMATEL) approach categorizes the critical Success factors into two classes: cause and effect. This is implemented by evaluating direct and indirect influences among critical Success factors. In accordance with Section 3.5.1's procedure, seven experts' opinions on 15 CSFs are recorded in the form of impact matrices (Appendix A 8), and an average matrix, Z, is derived using Equation 3.12. On top of that, we can use Equation 3.13 to calculate a normalised version of the initial direct-influence matrix, N. Z, the average influence matrix, and N, the normalised initial direct-influence matrix, are presented in Tables 5.9 and 5.10, respectively. Table 5.11 displays the results of the DEMATEL method's calculation of the total impact matrix, Y, using Equation 3.14.

Table 5.12 displays the results of applying Equation 3.15 to the rows sum vector (SR), columns sum vector (SC), SR + SC vector, and SR - SC vector of matrix Y. Table 5.12 also displays the values for (SR - SC), which are used to rank the critical success factors. In addition, Figure 5.3 provides a summary of the DEMATEL method's findings organised according to causal relationships. A total of eight critical success factors belonging to the cause group are found, all of which have direct effects on other critical success factors belonging to the impact group, based on the criterion of the positive score of (SR - SC). There are a number of factors that contribute to BDA not being implemented, including a lack of a contract agreement among stakeholders, a lack of top-level commitment and engagement, an inability to handle big data, an inability to identify and solve problems, a lack of a strategy for BDA, a lack of quality data, a lack of competent decision-makers, and an inability to integrate customer needs with a performance framework. These important success factors for the cause group might be thought of as external, unrelated elements that have a significant impact on the business. In order to successfully implement BDA in the manufacturing sector, more focus must be given to these crucial success factors.

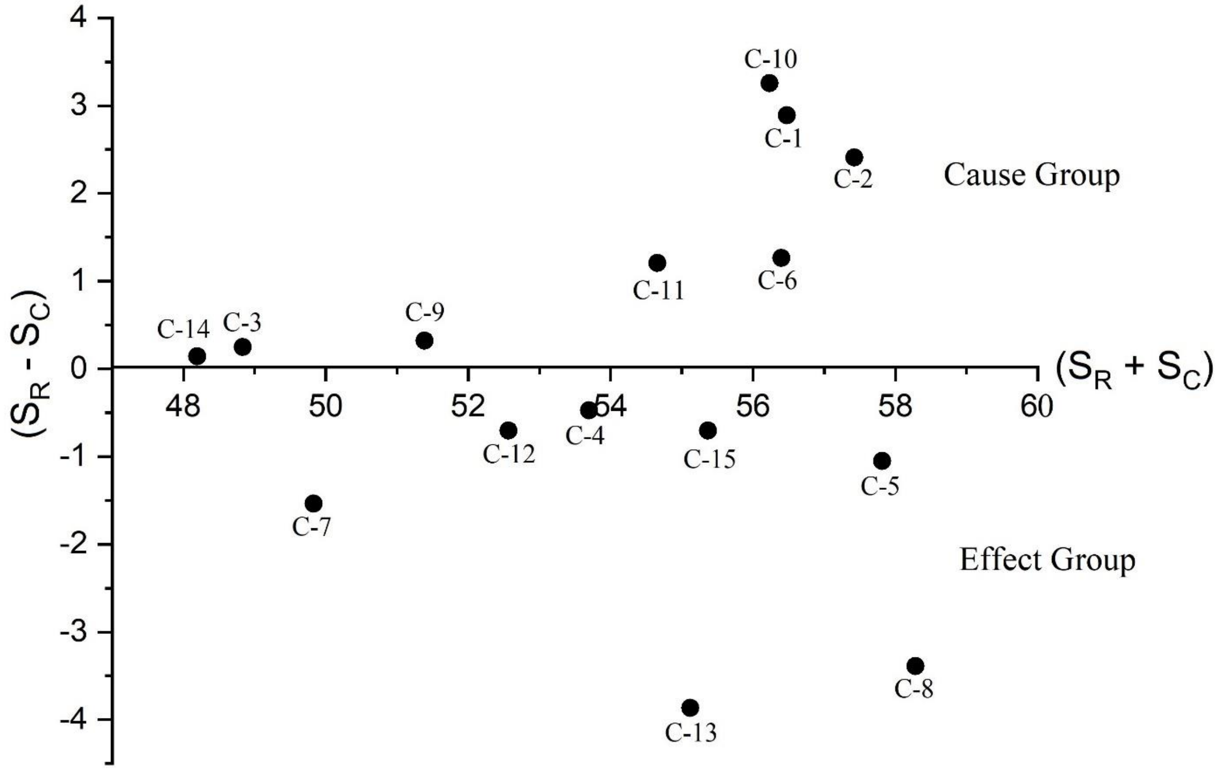

Figure 5.3 The Causal Diagram for Critical Success Factors (Source: Self)

The availability of quality and reliable big data has the highest (S_R - S_C) score and is the most crucial cause with the highest direct impact on the other critical success factors. Based on (S_R - S_C) score development of contract agreement among all stakeholders and the commitment and engagement of top management are placed at the second and third highest positions in cause group CSFs. This suggests that the development of contract agreements among all stakeholders and top management engagement are necessary for implementing BDA in manufacturing organizations. Problems identified and solving capabilities, with (S_R - S_C) score of 1.262, has the fourth position pointing to the importance of BDA in the manufacturing sector. Further, the knowledgeable and capable decision-makers with (S_R - S_C) score of 1.2016 is an important factor that will help make the right decisions for the organization. Next, 'Strategy development for BDA, with (S_R - S_C) score of 0.3199, will aid in strategy development. The development of capability for handling big data, with (SR - SC) score of 0.2464, is another crucial factor ensuring data handling. Integrating customer requirements with a performance framework have the eighth rank with the smallest (S_R - S_C) score (0.14178).

There is a similarity to a certain extent in drawing inferences from the Fuzzy TOPSIS, and DEMATEL approaches. The top five critical success factors, as ranked by Fuzzy TOPSIS, also fall in the cause group identified by the DEMATEL approach. Therefore, management should give more attention to these independent factors as they have a crucial role in implementing BDA for manufacturing organizations. Further, based on the negative (S_R - S_C) values seven critical Success factors fall in the effect group. The effect group factors are: Robust cybersecurity system, coordination among big data stakeholders, process integration and institutionalization, flexible digital infrastructure, data-driven organization culture, process monitoring and control, and responsive information sharing framework. These CSFs were most affected by the other critical success factors.

Table 5.7 Weighted Normalized Fuzzy Matrix (V)

	1			2			3			4			5			6			7		
C-1	0.016	0.02	0.022	0.02	0.06	0.1	0.047	0.06	0.067	0.027	0.045	0.063	0.017	0.052	0.086	0.003	0.01	0.017	0.029	0.088	0.147
C-2	0.016	0.02	0.022	0.141	0.181	0.201	0.047	0.06	0.067	0.045	0.063	0.081	0.052	0.086	0.121	0.017	0.024	0.031	0.147	0.206	0.265
C-3	0.016	0.02	0.022	0.141	0.181	0.201	0.02	0.033	0.047	0.045	0.063	0.081	0.052	0.086	0.121	0.017	0.024	0.031	0.147	0.206	0.265
C-4	0.007	0.011	0.016	0.06	0.1	0.141	0.007	0.02	0.033	0.045	0.063	0.081	0.017	0.052	0.086	0.01	0.017	0.024	0.088	0.147	0.206
C-5	0.007	0.011	0.016	0.1	0.141	0.181	0.047	0.06	0.067	0.009	0.027	0.045	0.052	0.086	0.121	0.01	0.017	0.024	0.029	0.088	0.147
C-6	0.011	0.016	0.02	0.1	0.141	0.181	0.047	0.06	0.067	0.045	0.063	0.081	0.121	0.155	0.172	0.017	0.024	0.031	0.206	0.265	0.294
C-7	0.016	0.02	0.022	0.1	0.141	0.181	0.047	0.06	0.067	0.045	0.063	0.081	0.052	0.086	0.121	0.017	0.024	0.031	0.088	0.147	0.206
C-8	0.011	0.016	0.02	0.1	0.141	0.181	0.033	0.047	0.06	0.027	0.045	0.063	0.017	0.052	0.086	0.024	0.031	0.035	0.088	0.147	0.206
C-9	0.016	0.02	0.022	0.141	0.181	0.201	0.033	0.047	0.06	0.027	0.045	0.063	0.121	0.155	0.172	0.017	0.024	0.031	0.147	0.206	0.265
C-10	0.011	0.016	0.02	0.141	0.181	0.201	0.02	0.033	0.047	0.027	0.045	0.063	0.017	0.052	0.086	0.017	0.024	0.031	0.147	0.206	0.265
C-11	0.011	0.016	0.02	0.141	0.181	0.201	0.007	0.02	0.033	0.045	0.063	0.081	0.052	0.086	0.121	0.017	0.024	0.031	0.088	0.147	0.206
C-12	0.007	0.011	0.016	0.1	0.141	0.181	0.033	0.047	0.06	0.027	0.045	0.063	0.052	0.086	0.121	0.01	0.017	0.024	0.088	0.147	0.206
C-13	0.011	0.016	0.02	0.06	0.1	0.141	0.033	0.047	0.06	0.045	0.063	0.081	0.086	0.121	0.155	0.01	0.017	0.024	0.088	0.147	0.206
C-14	0.011	0.016	0.02	0.06	0.1	0.141	0.02	0.033	0.047	0.027	0.045	0.063	0.052	0.086	0.121	0.01	0.017	0.024	0.088	0.147	0.206
C-15	0.002	0.007	0.011	0.06	0.1	0.141	0.007	0.02	0.033	0.027	0.045	0.063	0.017	0.052	0.086	0.003	0.01	0.017	0.088	0.147	0.206

Table 5.8 Closeness Coefficient Matrix and Ranking of Critical Success Factors (C)

Abbreviation	Critical Success factors for BDA implementation	D^+	D^-	C	Ranking
C-1	Development of contract agreement among all stakeholders	6.67038	0.3521	0.05014	15
C-2	Commitment and engagement of top management	6.33759	0.75235	0.10612	1
C-3	Development of capability for handling big data	6.39095	0.72115	0.1014	3
C-4	Robust cybersecurity system	6.64735	0.42696	0.06035	13
C-5	Coordination among big data stakeholders	6.4504	0.62222	0.08798	8
C-6	Problems identification and solving capabilities	6.44129	0.62757	0.08878	7
C-7	Process Integration and institutionalization	6.43448	0.63192	0.08943	6
C-8	Flexible digital infrastructure	6.46666	0.612	0.08646	9
C-9	Strategy development for BDA	6.36313	0.73731	0.10384	2
C-10	Availability of quality and reliable big data	6.39781	0.71702	0.10078	4
C-11	Knowledgeable and capable decision-makers	6.42569	0.70278	0.09859	5
C-12	Data-driven organization culture	6.47577	0.60665	0.08566	10
C-13	Process monitoring and control	6.58347	0.46553	0.06604	11
C-14	Integrating customers’ requirements with performance framework	6.61085	0.44798	0.05957	12
C-15	Responsive information sharing framework	6.65639	0.42163	0.06346	14

Table 5.9 Average Direct Influence Matrix (Z)

	C-1	C-2	C-3	C-4	C-5	C-6	C-7	C-8	C-9	C-10	C-11	C-12	C-13	C-14	C-15
C-1	0	2	2	2.5714	1.5714	3	2	2.7143	1.7143	1.8571	2.4286	3	2.5714	2.5714	2.1429
C-2	2.2857	0	2.1429	2	2.2857	2.5714	2.4286	3.1429	2.7143	2.5714	1.7143	2.1429	2.5714	1.7143	2.1429
C-3	2	2.4286	0	1.7143	2.1429	2	1.5714	2.7143	1.4286	1.2857	2	1.4286	2	1.4286	2
C-4	2	1.2857	2.4286	0	2.4286	2.2857	2.1429	2.4286	2.1429	2.5714	2.1429	0.8571	2.4286	1	2.4286
C-5	1.5714	2.1429	1.8571	1.5714	0	2.8571	1.5714	2	2	2.4286	2	3	2.2857	2.8571	2.5714
C-6	2.1429	2.4286	1.8571	2.5714	2.1429	0	2.1429	2.2857	1.8571	2.2857	2.5714	2.4286	2.7143	1.7143	2
C-7	1.8571	1.8571	1.7143	2.4286	2	1.4286	0	2	1.2857	1.5714	1.7143	2.5714	2.1429	1.2857	2
C-8	2.2857	2.1429	2.2857	2.7143	1.8571	2.1429	1.4286	0	2.1429	1.8571	2	1.4286	2.5714	1.8571	2.8571
C-9	1.7143	2	2	2	2.2857	1.1429	2	2.7143	0	2.5714	1.5714	1.5714	2.7143	2.1429	1.4286
C-10	2.2857	2.7143	2	2.2857	2.2857	2.1429	2.4286	2.7143	2.5714	0	2.5714	2.5714	0.5714	2	3
C-11	2.2857	2	2.1429	2.2857	2.1429	2.7143	2	2.1429	1.7143	1.8571	0	2.5714	2.1429	1.8571	2.2857
C-12	2.2857	0.8571	1.2857	1.8571	2.8571	2.2857	2.2857	2	1.5714	2.7143	2.7143	0	2.4286	1.1429	1.4286
C-13	2	2.8571	1.1429	2	2.5714	1.7143	2.4286	2.1429	2.4286	0.7143	1.4286	2.4286	0	1.8571	1.8571
C-14	2	1.8571	1.5714	1.7143	2.8571	1.2857	1.2857	1.7143	2	2.1429	2.1429	1.2857	1.8571	0	2
C-15	2.1429	3	1.57.14	1.4286	2.5714	2	1.8571	2.8571	1.7143	2.1429	1.8571	1.2857	2.7143	2.1429	0

Table 5.10 **N**ormalized Initial Direct Influence Matrix (N)

	C-1	C-2	C-3	C-4	C-5	C-6	C-7	C-8	C-9	C-10	C-11	C-12	C-13	C-14	C-15
C-1	0	0.066	0.066	0.0849	0.0519	0.0991	0.066	0.0896	0.0566	0.0613	0.0802	0.0991	0.0896	0.0849	0.0708
C-2	0.0755	0	0.0708	0.066	0.0755	0.0849	0.0802	0.1038	0.0896	0.0849	0.0566	0.0708	0.0849	0.0566	0.0708
C-3	0.066	0.0802	0	0.0566	0.0708	0.066	0.0519	0.0896	0.0472	0.0425	0.066	0.0472	0.066	0.0472	0.066
C-4	0.066	0.0425	0.0802	0	0.0802	0.0755	0.0708	0.0802	0.0708	0.0849	0.0708	0.0283	0.0802	0.033	0.0802
C-5	0.0519	0.0708	0.0613	0.0519	0	0.0943	0.0519	0.066	0.066	0.0802	0.066	0.0991	0.0755	0.0943	0.0849
C-6	0.0708	0.0802	0.0613	0.0849	0.0708	0	0.0708	0.0755	0.0613	0.0755	0.0849	0.0802	0.0896	0.0566	0.066
C-7	0.0613	0.0613	0.0566	0.0802	0.066	0.0472	0	0.066	0.0425	0.0519	0.0566	0.0849	0.0708	0.0425	0.066
C-8	0.0755	0.0708	0.0755	0.0896	0.0613	0.0708	0.0472	0	0.0708	0.0613	0.066	0.0472	0.0849	0.0613	0.0943
C-9	0.0566	0.066	0.066	0.066	0.0755	0.0377	0.066	0.0896	0	0.0849	0.0519	0.0519	0.0896	0.0708	0.0472
C-10	0.0755	0.0896	0.066	0.0755	0.0755	0.0708	0.0802	0.0896	0.0849	0	0.0849	0.0849	0.0189	0.066	0.0991
C-11	0.0755	0.066	0.0708	0.0755	0.0708	0.0896	0.066	0.0708	0.0566	0.0613	0	0.0849	0.0708	0.0613	0.0755
C-12	0.0755	0.283	0.0425	0.0613	0.0943	0.0755	0.0755	0.066	0.0519	0.0896	0.0896	0	0.080 2	0.0377	0.0472
C-13	0.066	0.0943	0.0377	0.066	0.0849	0.0566	0.0802	0.0708	0.0802	0.0236	0.0472	0.0802	0	0.0613	0.0613
C-14	0.066	0.0613	0.0519	0.0566	0.0943	0.0425	0.0425	0.0566	0.066	0.0708	0.0708	0.0425	0.0613	0	0.066
C-15	0.0708	0.0991	0.0519	0.0472	0.0849	0.066	0.0613	0.0943	0.0566	0.0708	0.0613	0.0425	0.0896	0.0708	0

Table 5.11 Total Direct Influence Matrix (Y)

	C-1	C-2	C-3	C-4	C-5	C-6	C-7	C-8	C-9	C-10	C-11	C-12	C-13	C-14	C-15
C-1	1.8935	2.0044	1.7778	1.9927	2.1296	2.0385	1.8768	2.2602	1.8575	1.9292	1.9633	1.9719	2.167	1.7746	2.0463
C-2	1.9778	1.9592	1.7961	1.9914	2.1652	2.0409	1.9033	2.2908	1.9012	1.9643	1.9564	1.9629	2.1787	1.7648	2.0627
C-3	1.6271	1.6818	1.4196	1.6362	1.7845	1.6735	1.5494	1.8843	1.5372	1.588	1.6224	1.6013	1.7861	1.4493	1.7002
C-4	1.7587	1.7861	1.6138	1.7161	1.9375	1.8166	1.6929	2.0283	1.6835	1.7548	1.7582	1.7166	1.9421	1.5558	1.8515
C-5	1.8599	1.9244	1.6978	1.8786	1.9897	1.9485	1.7848	2.1446	1.7872	1.8648	1.8683	1.8901	2.0622	1.71	1.9718
C-6	1.9049	1.9615	1.725	1.9375	2.0858	1.8927	1.8295	2.1863	1.8105	1.8878	1.9124	1.9028	2.1064	1.7019	1.9861
C-7	1.5977	1.6376	1.4496	1.6309	1.7537	1.6308	1.4766	1.834	1.5085	1.572	1.5897	1.6093	1.7617	1.4211	1.6732
C-8	1.8205	1.8644	1.6577	1.8517	1.9806	1.8673	1.7234	2.0157	1.7348	1.7878	1.8072	1.784	2.0061	1.6278	1.9184
C-9	1.7021	1.7552	1.557	1.7288	1.8814	1.733	1.6422	1.98	1.5725	1.7075	1.6933	1.6884	1.8961	1.5451	1.7717
C-10	1.9674	2.0289	1.7831	1.9879	2.1535	2.0187	1.8923	2.2666	1.8856	1.8779	1.9711	1.9633	2.1099	1.7631	2.0761
C-11	1.8516	1.8903	1.681	1.8711	2.0228	1.9162	1.7697	2.116	1.7508	1.8191	1.7774	1.8496	2.0276	1.6547	1.9338
C-12	1.7237	1.7266	1.5404	1.7306	1.9025	1.7733	1.6561	1.964	1.6252	1.7169	1.733	1.6475	1.8935	1.5209	1.7769
C-13	1.6955	1.7628	1.5185	1.7137	1.8738	1.7351	1.6411	1.9467	1.632	1.6417	1.6744	1.6993	1.8014	1.5235	1.7666
C-14	1.6028	1.6409	1.4473	1.611	1.7798	1.6281	1.5182	1.8278	1.5316	1.5904	1.6032	1.5743	1.7539	1.3842	1.6756
C-15	1.8091	1.8819	1.63	1.8077	1.9927	1.8559	1.7286	2.0931	1.7164	1.7887	1.7954	1.7751	2.0014	1.6307	1.8249

Table 5.12 Categorization of Critical Success Factors in the Cause-and-Effect Group

Critical Success factors	R	C	$(S_R + S_C)$	$(S_R - S_C)$	Ranking of CSFs based on $(S_R - S_C)$	Causes and effects
C-1	29.6834	26.7922	56.4756	2.89118	Second	Cause
C-2	29.9156	27.5061	57.4217	2.40945	Third	Cause
C-3	24.5409	24.2945	48.8354	0.24644	Seventh	Cause
C-4	26.6126	27.0862	53.6988	-0.4737	Ninth	Effect
C-5	28.3826	29.4331	57.8157	-1.0505	Twelfth	Effect
C-6	28.831	27.569	56.4	1.262	Fourth	Cause
C-7	24.1463	25.6849	49.8311	-1.5386	Thirteenth	Effect
C-8	27.4473	30.8384	58.2857	-3.3911	Fourteenth	Effect
C-9	25.8544	25.5345	51.389	0.31992	Sixth	Cause
C-10	29.7454	26.4909	56.2363	3.25446	First	Cause
C-11	27.9318	26.7257	54.6575	1.20616	Fifth	Cause
C-12	25.9311	26.6364	52.5675	-0.7053	Eleventh	Effect
C-13	25.6262	29.494	55.1201	-3.8678	Fifteenth	Effect
C-14	24.1692	24.0274	48.1966	0.14178	Eighth	Cause
C-15	27.3315	28.0359	55.3675	-0.7044	Tenth	Effect

5.5 Summary of Chapter

In this chapter, modeling of critical success factors for big data analytics implementation has been done. Based on expert opinion, researchers justify BDA applications in manufacturing using the Analytic hierarchy process (AHP). Further, critical success factors for BDA implementation are ranked by fuzzy TOPSIS. It has been found that commitment and engagement of top management, development of Capability for handling big data, strategy development for BDA, knowledgeable and capable decision-makers, availability of quality and reliable data, process integration, and institutionalization are the major strategic factors for successful implementation of BDA in manufacturing. Commitment and engagement of top management is the most important factor as the top management plays an important role in implementation of BDA and other supporting technologies that may ensure the benefits identified in the study. Finally, the DEMATEL approach is used to categorize strategic factors in terms of cause and effect. Availability of quality and reliable big data, commitment, and engagement of top management, development of contract agreement among all stakeholders are major factors in the cause category. This information of cause factors will help managers to prioritize the actions for the implementation of BDA. In the next chapter, the framework for TOE and DOI theories has been developed after taking the inputs from the previous studies and expert opinion. Further hypotheses development and testing for the proposed framework TOE and DOI theories will be discussed in the next chapter.

CHAPTER 6

HYPOTHESES DEVELOPMENT AND TESTING

This section is organised as follows: The “Introduction” section explains how manufacturers might benefit from big data. The outcomes of the earlier study on BDA adoption are discussed in the “BDA adoption in manufacturing” section. Section “Development of Hypotheses” details how researchers came at those hypotheses. “Questionnaire Development” section presents the detail of questionnaire development. “Results of Hypotheses Testing” section provides the detailed result of hypotheses testing. Finally, the summary of this chapter is provided in “Chapter Summary” section.

6.1 Introduction

Big data analytics (BDA), cyber-physical systems (CPH), cloud computing (CC), and the internet of things (IoT) are all crucial for businesses to use in the age of Industry 4.0. (Gupta et al., 2020). The term “big data” is used to describe the huge amounts of data that may be found within a company, and which are generated at extremely rapid rates (Gandomi and Haider, 2015). In other words, it is challenging to store, handle, and analyse a vast and massive data collection using conventional data processing techniques. BDA refers to the advanced technologies that abstract hidden information from massive data sets that helps in real-time decision-making (Mcafee and Brynjolfsson 2012). BDA helps enhance operational performance, improve decision-making capability, develop a product, and improve customer service (Gunasekaran et al., 2017). The BDA represents a change in the development of business practices, which is why organizations should consider the implementation of the BDA (OECD 2017); with the help of BDA, organizations can extract value from enormous amounts of data. Manufacturing industries deal with business difficulties by suing BDA (EPU, 2017). As a result, large organizations, and small and medium enterprises (SMEs) can benefit from using innovative technologies (Ghobakhloo et al., 2012).

In the age of digital integration, modern technologies such as smartphones and other electronic gadgets have become more affordable to capture, store, and analyze data (Alsghaier et al., 2017). Therefore, everyone is creating a ubiquitous and ever-increasing digital record, usually called big data (Rachinger et al., 2019). Big data is widely known as one of the pillars of future technology, capable of providing tremendous financial value to firms (Raguseo and Vitari, 2018).

Apart from these advantages of BDA, there is a lack of research on how organizations approach BDA adoption. Therefore, there is a lack of awareness of how organizations are involved in BDA utilization and value creation (Mikalef et al., 2019). However, most manufacturing industries are hesitant to employ BDA in their organizations due to a lack of awareness (Iqbal et al., 2018). For example, manufacturing industries are uncertain about implementing modern technologies due to a lack of IT infrastructure, insufficient skills, shaky top-management support, insufficient technologies to support large volumes of unstructured data, and a lack of financial support (Shin, 2016; Christina and Stephen, 2017). Figure 6.1 depicts the flow of this chapter.

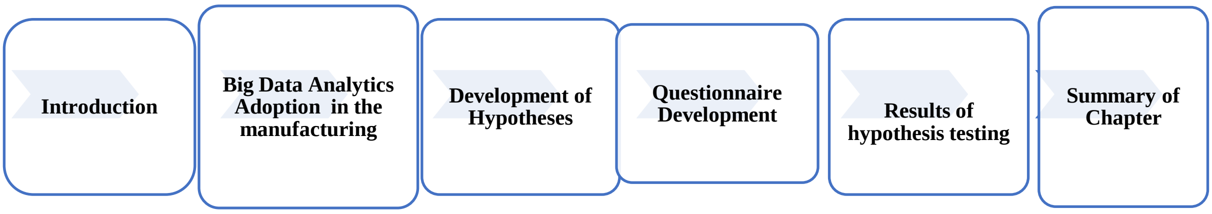

Figure 6.1 Chapter Flow Diagram

6.2 Big Data Analytics Adoption in the Manufacturing

Big data analytics has not yet been extensively used in the supply chain for actionable information. It is partially due to businesses' incapacity to analyze enormous amounts of data or to employ false information, which may incur additional expenditures and deliver no meaningful outcomes because of this insufficiency (Tiwari et al., 2018). While some industries are now benefiting from BDA to boost their BI and get a competitive edge, many others are still in the dark about what BDA is and how it might help them (Kwon et al., 2014). As a result, it is crucial for companies interested in implementing BDA in their supply chain operations to learn more about the drivers and roadblocks of BDA uptake. The literature on BDA adoption and the elements that contribute to it is lacking in empirical studies. That's why it's crucial to look into the factors that influence the decision to employ BDA in supply chain activities (Lai et al., 2018).

Some studies have previously been undertaken to investigate the factors influencing BDA adoption intentions. Among these studies is one by Verma and Chaurasia (2019), who used a survey questionnaire to investigate factors in the adoption of BDA by Indian enterprises. A number of factors were found to influence whether or not a group adopted new technology, such as relative advantage, competitive pressure, managerial support, technical readiness, compatibility, organisational data environment, and complexity. Using the Technology-Organization-Environment (TOE) theory and the Innovation Diffusion Theory (DOI), Lai et al. (2018) conducted a survey-based investigation (2018). The results demonstrated that environmental variables, such as government laws and the use of BDA by competitors, were significant moderators of adoption of the approach in the firms that participated in the study, in addition to senior management support and relative advantage. Based on interviews with 22 firms in India, Verma and Bhattacharyya (2017) found these inhibitors: a lack of strategic value in BDA and an unwillingness to execute due to TOE challenges. BDA adoption in India is influenced by the regulatory environment, according to a study conducted by Agrawal (2015). Agrawal found that the legal framework has an effect on the rate of BDA adoption in India (2015). A survey of 161 American businesses indicated that relative advantage and technical expertise significantly impacted BDA adoption. Comparatively, the impact of environmental and organisational elements was indirect. Ramanathan et al. 2017 conducted research into the impact of environmental variables and BDA adoption drivers on firm performance. Studies of

BDA adoption at the organizational level are summarized in Table 6.1. For the purposes of data collection, analysis, and reporting, these studies exclusively considered organizations. Many of them have employed survey research to gauge public opinion. It is unclear if there are any supply chain-level research that may be utilised as a guide. Therefore, this study employed a qualitative methodology to inquire into the utilisation of BDA in manufacturing. Since the TOE framework was used, this research offers a conceptual framework for examining the factors affecting BDA adoption in manufacturers' supply chains. While surveys are the norm, this study takes a more in-depth look at BDA adoption aspirations through a qualitative approach based on in-person interviews. A review of the relevant literature revealed that prior research had not focused on a specific industry or evaluated the key participants in its supply chain in order to gain a comprehensive understanding of the latter.

Table 6.1 Previous Investigations into BDA Adoption

Authors	Research Objective	Country	Context	Methodology & Theory
Agrawal (2015)	The study of the variables that affect the adoption of BDA	China and India	Different sectors	Survey-based TOE framework
Chen et al. (2015)	The examination of the elements that influence the adoption of BDA	USA	Different sectors	TOE framework
Verma & Bhattacharya (2017)	The study of the variables that affect the adoption of BDA	India	Different sectors	Semi-structured interviews and TOE framework
Dubey et al. (2016)	The contribution of big data to the understanding of supply chain sustainability and disaster resilience	Italy	Supply chains for sustainability	TOSE framework

Ahmed, et al. (2017)	The function of BDA in Internet of Things	France	Different sectors	Survey-based
Ramanathan et al. (2017)	The investigation of the factors affecting the adoption of BDA	UK	Retail sector	Case studies and TOE model
Lai et al. (2018)	The study of the factors that affect the adoption of BDA	China	Different sectors	Survey-based TOE framework and DOI theory
Zhu et al. (2018)	The effect of operational supply chain transparency and supply chain analytics	Europe, Asia, USA	Different sectors	Survey-based Information processing theory
Verma & Chaurasia (2019)	The study of the factors that influence the adoption of BDA	India	Different sectors	Survey-based TOE framework
Janssen, M. et al. (2017)	Factors affecting the effectiveness of big data decision-making	Netherland	Different sectors	Case study
Maroufkhani (2020)	Big data analytics implementation model for SMEs	Malaysia	Different sectors	TOE Model
Alalawneh, and Alkhatib (2021).	The obstacles to big data adoption in developing countries	UK	Different sectors	AHP and TOPSIS

Virmani et al. (2020)	A emphasis on identification and testing of hurdles to sustainable production in the automobile industry.	India	Automobile Industry	EFA, CFA and GTMA
Ram et al. (2019)	Adoption of BDA in construction: development of a conceptual model	Australia and China	Construction Sector	TOE framework.
Bag et al. (2020)	BDA for operational excellence to enhance sustainable supply chain performance	South Africa	sustainable supply chain	PLS-SEM
Dubey et al. (2021)	Describe how the ability to use data analytics to improve organizational flexibility's moderating influence on supply chain resilience and competitive advantages.	India	Different Sector	Organizational information processing theory (OIPT)
Sun et al. (2020)	An integrated perspective of organizational desire to utilize big data in the B2B	China	Different Sector	TOE and DOE theory
Rakhman et al. (2019)	Implementing BDA in the Banking Sector: A Case Study of Cross-Selling in an Indonesian Commercial Bank	Indonesia	Banking Sector	Interviews and case study
Yasmin et al. (2020)	An integrated MCDM approach to BDA capabilities and company performance	Pakistan	Different Sector	IF-DEMATEL ANP and SAW

Gawankar et al. (2020)	Measures of organizational success, big data-driven supply chain investments, and Indian retail 4.0 context	India	Retail	SEM
Belhadi et al. (2020)	The combined impact of lean six sigma, green manufacturing, and BDA on a manufacturing company's environmental performance	North Africa	Manufacturing companies	Define-Measure-Analyze-Improve-Control (DMAIC) framework
Nozari et al. (2021)	BDA of IoT-based supply chain management considering FMCG industries	Iran	*Fast-moving consumer goods* (*FMCG*) *sector*	Smart business based on IoT

6.2.1 Technology–Organization–Environment Theory

Adoption problems with BDAs were analysed using the Technology-organization-environment (TOE) framework (Priyadarshinee et al., 2017). In order to provide a theoretical basis for the widespread adoption of innovation in the business world, Tornatzky et al. (1990) presented a mode. It is a broad indicator of the various enabling variables (technological, organisational, and environmental) for implementing new technologies. Organizational context is reflected in the descriptive parameters such firm size, financial resources, and organisational structure (Alsaad et al., 2017). Competition from outside sources, as well as restrictions imposed by the government, all make up what is known as an organization's "environmental context" (Oliveira and Martins, 2011; Alshamaila et al., 2013). For quite some time, the Technology Adoption Lifecycle (TOE) hypothesis has held the title of "most popular theory for the study of (Maduku et al., 2016). Because of this, the framework can be used to incorporate new technologies (Awa et al., 2015).

6.2.2 Diffusion of Innovations Theory

Innovation refers to a new concept, activity, or object experienced by an individual adoption (Rogers 1995). According to DOI theory, five characteristics (i.e., Awareness, persuasion, decision, implementation, and continuation) influence new technology adoption. These five characteristics are essential in helping organizations adopt innovative technologies (Albar and Hoque, 2019, Rogers 2003). One of the most significant innovation aspects influencing the IT adoption rate is a relative advantage compared to the traditional manufacturing system. Compatibility is the most critical component of innovation adoption using information systems (Premkumar 2003). The main impediment to modern technology adoption is its complexity (Premkumar and Ramamurthy 1995).

6.3 Development of Hypotheses

The manufacturing sector has started to invest in BDA as a result of the rise of digitization. But there are several challenges in the way of fully implementing BDA. The organisational principles of TOE and DOI are displayed in Figure 6.2. Manufacturing organisations are beginning to see the benefits of incorporating the BDA into their supply chain operations (including logistics, purchasing, planning, and inventory management) (Wang et al., 2016b). BDA can be used to solve optimization challenges in resource planning and usage, which are crucial to the efficiency of the supply chain (Bag et al., 2020). Based on their research into the use of corporate data analytics in various sectors, Zhong et al. (2016) stated that intelligent cloud-based infrastructure would be at the centre of future BI efforts. Intelligent processors that can generate new processing methods on the fly to accommodate new processing requirements, as well as collaboration and collaborative services, will be made possible by advances in processing technology. The literature analysis uncovered a number of factors that affect the rate of big data analytics adoption in the industrial industry. The following hypotheses were so generated and tested.

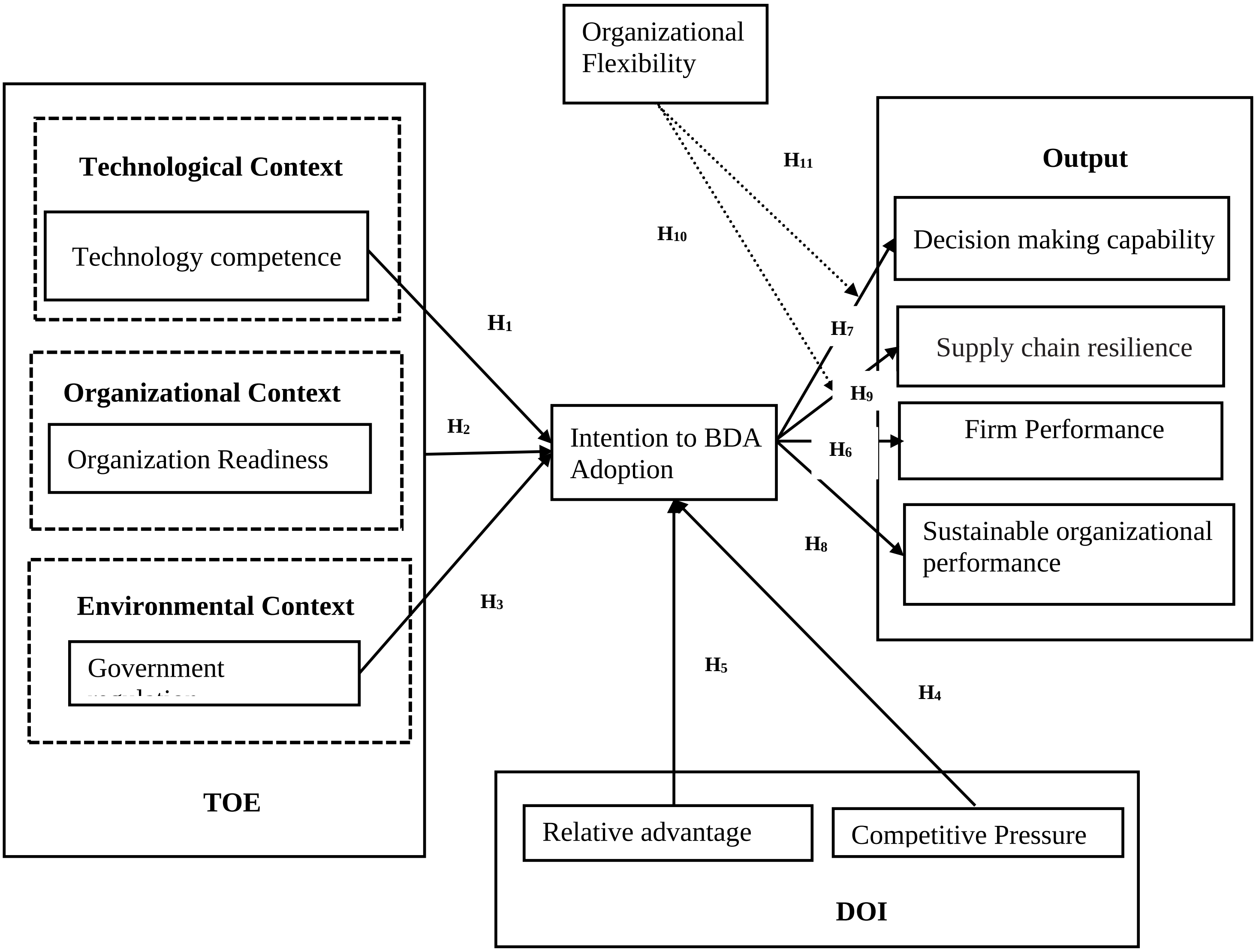

Figure: 6.2 Conceptual Frameworks of TOE and DOI Theories (Source: Self)

- ***Technology competence (TC):***

In this study, technological competence refers to the firm's capability to use modern technology effectively to enhance the organization's performance (Bharadwaj, 2000). Successful acceptance of modern technology depends on the level of compliance between the features of modern technology and the firm’s existing infrastructure. The company's IT infrastructure somehow controls the speed of adoption. A company with a wide range of technical resources can provide a platform to help implement modern technologies, while the lack of appropriate technical resources makes the acquisition process more difficult. To this, the following hypotheses is proposed:

Hypothesis- 1 **(H_0):** Technological competence will not positively affect an organization's intention to adopt BDA.

Hypothesis- 1 (H1): Technological competence will positively affect an organization's intention to adopt BDA.

- ***Organizational Readiness (OR):***

Organizational readiness refers to the availability of resources in terms of technology, money, and people (Zhu et al., 2006). Technological resources have the necessary tools, technical platforms, software, data processing, and evaluating available data. An organization's ability to pay for the installation of its information systems and recurring expenses during its use and maintenance cycle is referred to as financial resources. Human resources give the knowledge and skills required to carry out technological initiatives. As a result, organizational readiness refers to a business's ability to integrate modern technologies like BDA. The following hypothesis is proposed based on the above discussion:

Hypothesis- 2 **(H_0):** Organizational readiness will not positively associate with BDA adoption.

Hypothesis-2 (H1): Organizational readiness is positively associated with BDA adoption.

- ***Government regulation (GR):***

Government regulation is another critical component of BDA adoption (Weigelt and Sarkar, 2009). Restrictions and rules are examples of government regulations. These restrictions may sometimes push the organization to implement modern technology. According to Tornatzky et al. (1990), government laws for technology adoption may require firms to have some preconditions, such as technical standards, which might increase the cost of adopting modern technology. Thus, the following hypothesis is proposed:

***Hypothesis- 3* (H$_0$):** Government regulations will not positively affect the intention to adopt BDA

Hypothesis-3 (H1): Government regulations positively affect the intention to adopt BDA.

- ***Competitive Pressure (CP):***

The literature is unanimous in its recognition of the role that competitive pressure plays in driving the adoption of cutting-edge technologies (Lian et al., 2014). The term is used to describe the pressure an organisation is under from its rivals (Zhu and Kraemer, 2005). Due to better market visibility and the capacity to make quick decisions, BDA adoption can lead to increased operational efficiency and precise forecasts (De Oliveira et al., 2012; Gandomi and Haider, 2015). Consequently, the following conjectures are advanced:

***Hypothesis- 4* (H$_0$):** Competitive pressure does not have positively influences Big Data adoption.

Hypothesis- 4 (H1): Competitive pressure positively influences Big Data adoption.

- ***Relative Advantage (RA):***

Relative advantages associated with modern technologies over existing technologies play a significant role in their adoption. It refers to the level at which technology is considered to provide more benefit to organizations (Wang and Wang 2016). As a result, the prospects for adoption are likely to increase as organizations see the benefits of modern technologies. It also stimulates the development of innovative ideas and business models and more information transparency. Although BDA technologies are initially costly, they access enormous amounts of data intelligently and at high speeds, resulting in a long-term, cost-effective strategy. BDA also provides more options for gaining a competitive advantage. Further, BDA aids firms in gaining a better understanding of how others perceive their products. Therefore, we propose:

***Hypothesis- 5* (H$_0$):** Relative advantage does not have influences Big Data adoption positively.

Hypothesis- 5 (H1): Relative advantage influences Big Data adoption positively.

- ***Firm Performance (FP):***

A company's financial and market performance is referred to as the firm's performance. Market performance is linked to an organization's ability to strengthen its market position to gain a competitive advantage, whereas financial performance is linked to revenue growth and profitability (Ren et al., 2017). Compared to competitors, profitability, expansion, cost reduction, and lead time are benefits from BDA deployment (Mikalef et al., 2019). Raut et al. (2019) show that BDA can improve a company's performance by increasing tangible or intangible productivity. Consequently, a firm with higher BDA capabilities can get the best performance. Firms that make efficient use of big data are better able to translate data into actionable information. BDA can improve operational performance, product/service development, and human resource (Kumar et al.2021). Thus, the following hypotheses are proposed:

***Hypothesis- 6* (H$_0$):** BDA adoption will not influence the organization's financial performance.

Hypothesis- 6 (H1): BDA adoption influences the organization's financial performance.

- ***Decision Making capability (DMC):***

Decision Making capability shows decision-related skills to reach the best outcome. The level at which investment decision-making about BDA resources is structured according to formal and informal procedures. According to McAfee et al. (2012), a data-driven decision-making culture is one in which senior executives make decisions based on data rather than intuition. Top management support as well as adequate technical and managerial capabilities play a significant role for the successful implementation of BDA (Waller and Fawcett, 2013). Thus, the following hypotheses are proposed:

***Hypothesis- 7* (H_0):** BDA adoption will not positively influence decision-making capability.

Hypothesis- 7 (H1): BDA adoption positively influences decision-making capability.

- ***Sustainable* organizational performance (SOP):**

For sustainable organizational performance, big data plays a critical role. By taking valuable information from big data, organizations compete in an unpredictably competitive business environment (Salehan and Kim, 2016). As a result, firms are collecting information from big data to aid in sustainable products, reduce costs, and reduce the time to market (Tan and Zhan, 2017). In organizations, cultural and economic elements significantly impact long-term product development (Roy and Goll, 2014). Managers may find it helpful to use sustainable supply chain drivers and an awareness of how they relate to one another as an easy-to-follow framework for integrating sustainability components into a firm (Dubey et al., 2019). Based on the literature, lean approaches can help supply chain sustainability directly and indirectly (Bag et al., 2018a, Ruiz-Benitez et al., 2019). Hence, the following hypothesis is proposed:

***Hypothesis- 8* (H_0):** BDA does not have positively impacts sustainable organizational performance.

Hypothesis- 8 (H1): BDA positively impacts sustainable organizational performance.

- ***Supply chain resilience (SCR):***

The concept of SCR has gained substantial attention from operations management and is regarded as multidisciplinary. According to Adobor and McMullen (2018), supply chain interruptions can have significant economic consequences. Practitioners and policymakers are paying more attention to managing the risk associated with supply chains. It is a multidisciplinary concept, defined as a system's ability to deal with change (Chowdhury and Quaddus 2017). It has become a critical component of supply chain risk and vulnerability management (Adobor and McMullen 2018). Resilience has become increasingly significant in supply chain perspectives due to rise disruptions caused by unanticipated events (Ivanov and Sokolov 2018, Chowdhury and Quaddus 2017). According to a review of existing literature, collaboration among supply chain partners is critical for developing resilience by reducing the risk of interruption through information sharing in the event of an unexpected event. Sharing information on supply chain risk is crucial in a complex environment for enhancing resilience by reducing disruption risks and offering new business opportunities (Chowdhury and Quaddus 2017). Thus, the following hypotheses are proposed:

Hypothesis- 9 **(H_0):** Big data analytics does not have positively impacts supply chain resilience

Hypothesis- 9 (H1): Big data analytics positively impacts supply chain resilience.

- ***Organizational*** **Flexibility (OF):**

Rapid technological changes are occurring nowadays, which means that only firms that are flexible enough to adapt to modern technology attain a significant advantage. For example, an organization will also utilize technology, the organization should allow its staff to work remotely and collaborate virtually. Flexibility has been highlighted as an important organizational ability to adapt to highly unpredictable activities (Williams et al., 2014). Schilling and Steensma (2001) argued that managers should adapt their organizational structures and procedures to meet changing technology. This ability to adjust is referred to as organizational flexibility. Many distinct types of operational flexibility have been identified in a previous study (Sethi and Sethi, 1990). Thus, the following hypotheses are proposed:

Hypothesis- 10 **(H_0):** Organizational flexibility does not have positively moderates the relationship between intention for BDA adoption and SCR.

Hypothesis- 10 (H1): Organizational flexibility positively moderates the relationship between intention for BDA adoption and SCR.

Hypothesis- 11 **(H_0):** Organizational flexibility does not have positively moderates the relationship between intention to BDA adoption and decision-making capability

Hypothesis- 11 (H1): Organizational flexibility positively moderates the relationship between intention to BDA adoption and decision-making capability.

- ***Intention for BDA Implementation (BDAI):***

BDA adoption is uncertain until key stakeholders can innovatively extract new knowledge by combining structured and unstructured data from different processes/activities inside and outside the organization (Chen et al., 2012). However, without proper expertise, such creative thinking may be difficult to achieve within the organization. The utilization of BDA requires not just IT resources but also domain experts who can evaluate the results, identify development opportunities, and act based on information. Table 6.2 summarizes different constructs and items selected for this study. Based on the above discussion, a conceptual research framework was developed for this research work (refer to Figure 6.2).

Table 6.2 Construct's Description

Model	Constructs	Items	Abbreviation	Adopted from
	Technology competence (TC)	Our company has the competence to adopt new technology such as BDA.	TC1	Kuan and Chau, (2001), Wang et al., (2010)
		Our company has capability for adopting BDA.	TC2	
		Our company is well-versed in implementing big data analytics.	TC3	

TOE Adopted from Tornatzky and Fleischer (1990)		Our company has a good infrastructure for supporting BDA.	TC4	
	Organizational readiness (OR)	Our organization has sufficient resources for investing in BDA.	OR1	Chen et al. (2015)
		Our organization is ready to allocate adequate resources for adopting the BDA.	OR2	
		Our organization devotes sufficient financial support to upgrade employees' technical skills to implement BDA.	OR3	
		Our current organizational structure enables us to adopt the BDA.	OR4	
	Government regulation (GR)	The governmental policies encourage us to adopt BDA	GR1	Gupta and Barua (2016), Li (2008)
		The government provides incentives/support for using new technologies such as BDA in government procurements and contracts.	GR2	
		Government policies support the security and privacy concerns as a consequence of BDA application.	GR3	

DOI Rogers (1962)	Competitive Pressure (CP)	Our choice to invest in big data analytics is strongly influenced by what competitors are doing.	CP1	Lai et al., (2018), Iacovou et al. (1995)
		Our company feels pressure from the market; therefore, we are keen to adopt BDA.	CP2	
		Our competitors have begun to adopt BDA aggressively.	CP3	
		If our firm does not undertake big data, we may lose a competitive edge over competitors.	CP4	
	Relative Advantage (RA)	Our company believes that BDA could enhance our performance.	RA1	Chen et al. (2015), To and Ngai (2006), Premkumar and Ramamurthy (1995)
		Our company believes that BDA will provide timely information for decision-making.	RA2	
		Our company feels that big data analytics adoption would result in cost savings.	RA3	
		Our company believes that BDA could improve the customer service	RA4	
		We believe that BDA will increase profitability.	FP1	Tippins and Sohi (2003)

	Firm Performance (FP)	We believe that big data analytics will increase operational performance.	FP2	
		We believe that BDA will improve return on investment	FP3	
	Decision Making capability (DMC)	We believe that BDA is an asset for decision-making.	DMC1	George et al. (2014), Srinivasan, and Swink, (2015).
		We feel that our company will be able to use data for effective decision-making.	DMC2	
		We believe that our organization will be able take decisions effectively by adopting BDA.	DMC3	
		We continuously assess our strategies and take corrective action in response to the insights obtained from data.	DMC4	
	Sustainable organizational performance (SOP)	We believe that BDA will protect the environment by focusing on environmental quality and improving resource efficiency.	SOP1	Kirchherr et al. (2017), Law and Gunasekaran, A (2012)
		We believe that BDA will improve sustainable organizational performance.	SOP2	

		We believe that big data analytics will help minimize resource consumption.	SOP3	
	Supply chain resilience (SCR)	We believe that by adopting BDA, our organization can restore material flow after a disruption.	SCR1	Brandon-Jones et al. (2014)
		We believe that by implementing BDA, our organization would not take a long time to recover normal operating performance after a disruption.	SCR2	
		We believe that by investing in BDA, the supply chain would quickly recover to its original state.	SCR3	
		We believe that by adopting BDA, our organization will quickly deal with disruptions.	SCR4	
	Organizational Flexibility (OF)	Our organization can rapidly adjust our organizational structure, to adapt to supply chain disruptions.	OF1	Sethi and Sethi (1990); Upton (1994)
		Our organization can respond to supply chain disruptions cost-effectively.	OF2	

		Our organization is more flexible than our competitors in changing our organizational structure.	OF3	
	Intention for BDA Implementation (BDAI)	We firmly intend to use BDA in our company.	BDAI1	Esteves and Curto (2013).
		Our company is planning to invest in the adoption of BDA.	BDA2	
		Overall, we have a favorable attitude of employees towards BDA implementation.	BDAI3	

6.4 Questionnaire Development

The questionnaire was created to collect information from professionals in various fields so that it might be used for research and hypothesis testing. The questionnaire was developed with the help of a literature review and the advice of industry professionals. The questions for each latent component ranged in size from three to four. We used a 7-point Likert scale to rate the reflective markers (i.e., strongly disagree to agree strongly). Respondents in the Indian manufacturing sector provided the data. Nearly a thousand Indian professionals in their respective fields were polled for this study. Only 305 of the 1050 queries were successful. Companies in the manufacturing sector in the Delhi/National Capital Region (NCR) responded to the survey, with a response rate of about 29.04 percent (Refer to Figure 6.3). We emailed them and requested them to fill out the survey. Please see Appendices 9-10 for a comprehensive survey.

6.4.1 Data Collection

To further understand how BDA is being used in India's manufacturing industry, a survey based on questionnaires was undertaken. Those chosen to serve as experts came from both the private sector and the academic world. Research participants were asked to fill out a questionnaire tailored to their specific fields of expertise, both in and out of the classroom (Refer to Annexure 10). There are two segments to this survey. Two production managers, one marketing director, an operations engineer, a logistics director, and two professors make up the expert team. Experts in industries have worked in their field for over 10 years, while academics have spent over fifteen years in the classroom and lab.

6.4.2 Demographic Details of Respondents

According to the findings of the research and discussions with specialists in the field, a questionnaire was developed. The demographic details of respondents under the categories of type of organization, number of employees, respondents' designation, and work experience of respondents. The demographics of the respondents are listed in Table 6.3.

Table 6.3 Demographic Details of Respondents

Demographics	Frequency	Percentage
Type of Organizations		
Manufacturing	116	38.04
Service	104	34.09
Other	85	27.86
Number of Employees		
≤200	63	20.65
201-400	94	30.82
401-800	75	24.59
>800	73	23.93

Designation in Organization		
General Manager	84	27.54
Manager, Senior Analyst, etc.	62	20.32
Senior Engineering	88	28.85
Engineer	71	23.27
Work Experience		
≤10 years	86	28.19
11-20 years	98	32.14
>20 years	121	39.67

Refer Table 6.3, 38.04% of the respondents are from the manufacturing sector, 34.09% are from the service sector, and 27.86% of the respondents are from other fields. About 20.65% of respondents are from the organizations that had fewer than 200 employees. Approximately 30.82% were from organizations having employees between 201 and 400 and 23.93% from organizations having employee between 401 and 800.

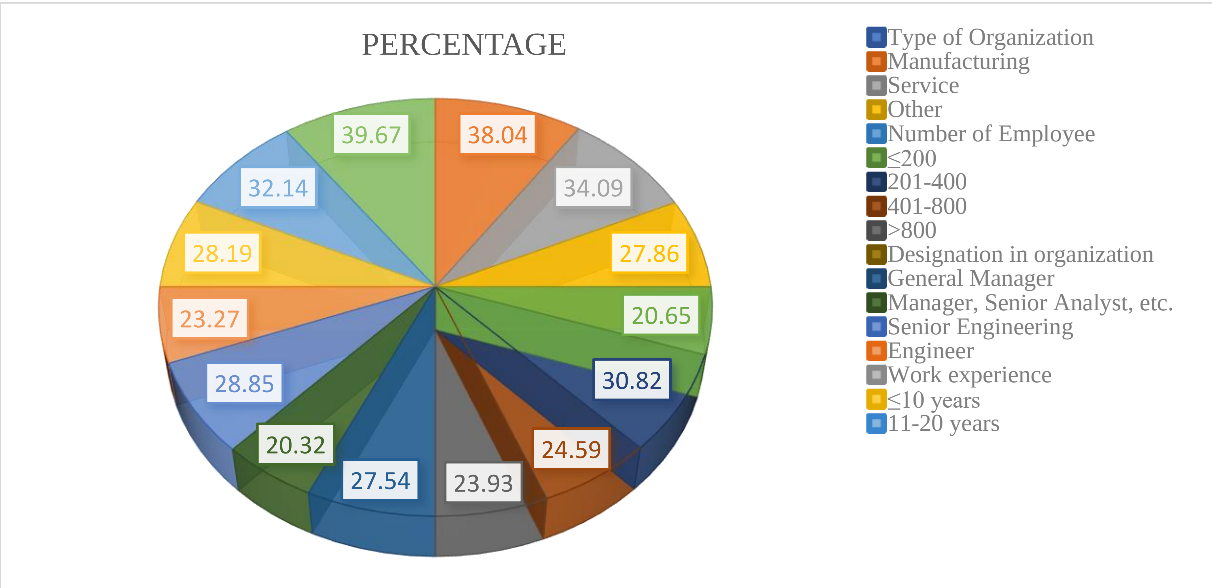

Figure 6.3 Respondents Summary

About 27.54% are senior managers or above, whereas 20.32 percent are managers, senior analysts, etc. A quarter of the staff are scientists and about a quarter are engineers. From the data presented above, we can infer that 28.19 percent of respondents have experience of 10 years or less, while 32.14 percent have experience of 11-20 years. The majority of responders (39.67%) have worked in their respective fields for more than 20 years.

6.4.3 Outliers and Missing Data

To ensure proper estimation; outlier data is removed before the quantitative analysis. According to Gaskin (2014), the observations made at the beginning and end of a Likert scale survey do not reflect outlier behavior. In a Likert scale survey, however, a responder may provide the same answer to most questions, and it should be excluding. In the present study, the researcher found four such observations while screening the data and excluded them from the study. Further checking for missing data is important in preparing data for quantitative analysis. As all the survey items were necessary, no missing data were detected in the collected data.

6.4.4 Data Validation/ Reliability Testing

The acquired primary response data is analysed using a variety of statistical techniques. Bartlett's test of sphericity is a correlation test used to validate the data. Data homogeneity is tested by this procedure. If the significance levels are less than 0.05, then factor analysis can be done with the data. The reliability analysis checks the stability of the factor information. This is done by calculating Cronbach's, a measure of reliability. To be reliable, a measure must have a Cronbach's A of less than 0.7. (Singh and Kumar, 2020). In addition, the KMO analysis is carried out to ensure that sufficient samples were collected. KMO value should be greater than 0.6, indicating that factor analysis may be suitable for data. These tests can easily be done by statistical software such as SPSS and Minitab.

6.4.5 Common Method Bias

The common method bias is examined and reported in the study after establishing the internal consistency, and construct validity of the measurement scale representing the BDA adoption by the selected organizations. The Harman single factor technique, in which EFA is conducted on the included statements with the assumption of one factor, is also used to investigate common method bias in the responses. The variation explained by the single factor is 38.5 %, which is less than 50%, according to the Harman single factor method's estimated results. As a result, the study can infer that the responses are free of common method bias and that all the study's conclusions are free of bias.

6.4.6 Convergent and Discriminant Validity Analysis

Creating a measurement scale that accounts for all of the components of interest in the investigation is the first step. The scale's convergent and discriminant validity, as well as its internal consistency according to the measurement model, were evaluated. Likewise, the validity of a scale relies heavily on the dependability of the equipment used to measure it. The dependability of an instrument is a measure of how consistently and accurately it can reproduce a given test result. In this work, employ Cronbach's α to evaluate internal consistency dependability, but other methods exist for doing so. Cronbach's alpha is useful for analysing the homogeneity of a scale's components and determining how well they correlate with one another (Bujang et al., 2018). Before analysing the interdependence of the measurement model, it is necessary to examine the measurement model to check the necessary construct validity and reliability level (Fornell & Larcker, 1981; Ifinedo, 2006).

Smart partial least square (SMART PLS) was used to analyse the construct and item diversity in the measurement model (see Figure 6.4). Table 6.4 displays the internal consistency (as evaluated by Cronbach's α), convergent validity (as indicated by correlations between items), and discriminant validity (as shown by scores on an alternate set of questions) of the measured model. Values of Cronbach's α between 0.70 to 0.91 indicate a good level of reliability, while values above 0.7 are regarded exceptional (Sekaran, 2003). Cronbach's α for all constructs except “Organizational flexibility” are within the range of 0.7 to 0.91, which is regarded to be a respectable level of reliability, suggesting that the various constructs contained in the measurement model have a good level of internal consistency. Cronbach's alpha values for all 39 items were also within the permitted range, showing that the items used were valid.

Composite reliability (CR) is a measure used to evaluate a construct's reliability and convergent validity. The appropriate scale reliability is indicated by a CR value larger than 0.7 (Nunnally & Bernstein, 1994). Table 6.4 shows that the composite reliability of each construct in the measurement model is greater than 0.70, indicating that all constructs in the measurement model representing the potential benefits of BDA in the manufacturing sector are reliable. The extent to which a construct's items converge or a significant proportion of variation is known as its convergent validity (Hair et al. 2010). Standardized construct loadings are used to evaluate convergent validity. The high standardized construct loadings imply that the construct components are meaningful and reflective of their construct. Standardized construct loadings to its observed variables should be more than 0.50. (Hair et al. 2010). All the observed variables in Table 6.3 have construct loadings ranging from 0.611 to 0.901. The findings indicate that the observed items appropriately and accurately reflect their constructs. The scale’s discriminant validity indicates how distinct a construct is from other constructs (Hair et al., 2010). For analyzing discriminant validity, the researchers use two methodologies.

The correlation coefficient between the multiple pairings of constructs in the measurement model, which are also theoretically different, should be low. These items are meant to be different from each other. Thus, they shouldn't be overly connected (Trochim, 2006). Second, the square root of average variances extracted (AVE) should be higher than the correlations between the constructs.

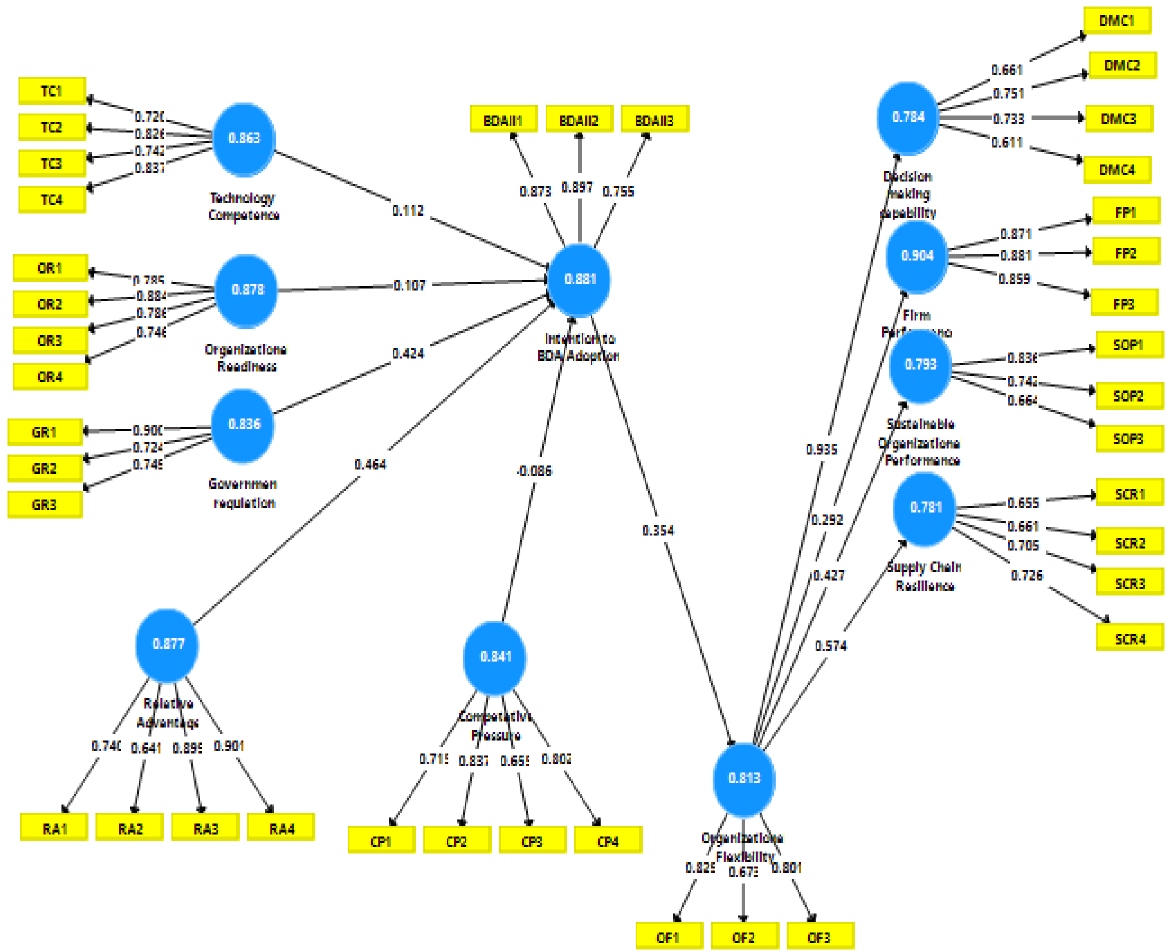

Figure 6.4 Measurement Model (Source: Self)

Since the AVE estimates of the various constructs in the measurement model are higher than the maximum shared variances of each construct. As all the constructs have a low correlation, these are independent. Furthermore, the estimated AVEs for the separate constructs exceed the inter-construct correlations (Refer to Table 6.5). Not only that, but the non-diagonal elements in the relevant rows and columns are larger than the square roots of the AVE shown in bold (See Table 6.5) for all the constructions. The results demonstrate that each construct is substantially linked with its items relative to other constructs in the measurement model. As a result, the suggested measurement model is found to have discriminant validity.

Table 6.4 Reliability and Validity Analysis

Construct	Items	Construct Loading	Cronbach Alpha	Composite Reliability	Average Variance Extracted
Technology Competence	TC1	0.720			
	TC2	0.826			
	TC3	0.742			
	TC4	0.837	0.794	0.863	0.613
Organizational Readiness	OR1	0.785			
	OR2	0.884			
	OR3	0.786			
	OR4	0.746	0.818	0.878	0.643
Government Regulation	GR1	0.901			
	GR2	0.724			
	GR3	0.749	0.707	0.836	0.632
Competitive Pressure	CP1	0.715			
	CP2	0.837			
	CP3	0.655			
	CP4	0.802	0.749	0.841	0.571
Relative Advantage	RA1	0.740			
	RA2	0.641			
	RA3	0.899			
	RA4	0.901	0.81	0.877	0.644
Firm Performance	FP1	0.871	0.842	0.904	0.757

	FP2	0.881			
	FP3	0.859			
Decision Making Capability	DMC1	0.661			
	DMC2	0.751			
	DMC3	0.733			
	DMC4	0.611	0.643	0.784	0.478
Sustainable Organizational Performance	SOP1	0.836			
	SOP2	0.742			
	SOP3	0.664	0.622	0.793	0.563
Supply Chain Resilience	SCR1	0.655			
	SCR2	0.661			
	SCR3	0.705			
	SCR4	0.726	0.659	0.781	0.472
Organizational Flexibility	OF1	0.829			
	OF2	0.673			
	OF3	0.801	0.652	0.813	0.594
Intention for BDA Implementation	BDAI 1	0.873			
	BDAI 2	0.897			
	BDAI 3	0.755	0.794	0.881	0.712

Table 6.5 Convergent and Discriminant Validity

	CP	DMC	FP	GR	BDAI	OF	OR	RA	SCR	SOP	TC
CP	**0.858**										
DMC	0.673	**0.935**									
FP	0.489	0.423	**0.902**								

GR	0.655	0.58	0.87	**0.951**							
BDAI	0.663	0.539	0.873	0.795	**0.93**						
OF	0.567	0.691	0.292	0.397	0.354	**0.77**					
OR	0.756	0.771	0.474	0.722	0.719	0.627	**0. 875**				
RA	0.637	0.475	0.963	0.916	0.844	0.336	0.608	**0.805**			
SCR	0.67	0.707	0.748	0.756	0.713	0.574	0.645	0.803	**0.687**		
SOP	0.498	0.499	0.688	0.664	0.599	0.427	0.448	0.677	0.644	**0.751**	
TC	0.754	0.749	0.509	0.721	0.725	0.595	0.802	0.6	0.615	0.533	**0.783**

6.5 Results of Hypotheses Testing

SMART PLS software was used to analyse the structural model, which was based on a postulated conceptual research model. The estimated values of the endogenous constructs' standard path coefficients (β), standard error, t statistics, and P-values are shown in Table 6.6. The level of statistical significance (α) is 0.05. Table 6.6 also displays the results of the hypothesis testing, with each beta coefficient describing the relative importance of the influencing factor. The P value is within the allowable range (P0.005), and all of the path coefficients are positive. Because of this, it may be concluded that the findings corroborated the hypothesis.

Table 6.6 Results of Hypotheses Testing for BDA Implementation

Endogenous Construct	Exogenous Construct	Standard Error	T Statistics	P Values	R Square	Decision
Competitive Pressure	Intention for BDA Implementation	0.034	2.513	0.014	63.7%	Supported
Government Regulation	Intention for BDA Implementation	0.043	9.919	0.000	68.4%	Supported
Intention for BDA Implementation	Organizational Flexibility	0.054	6.556	0.000	61.3%	Supported
Organizational Readiness	Decision Making Capability	0.006	16.355	0.000	62.4%	Supported
Organizational Flexibility	Firm Performance	0.062	4.676	0.000	64.4%	Supported
Organizational Flexibility	Supply Chain Resilience	0.04	14.428	0.000	64.4%	Supported
Organizational Flexibility	Sustainable Organizational Performance	0.051	8.381	0.000	64.4%	Supported
Organizational Readiness	Intention for BDA Implementation	0.036	2.956	0.004	62.4%	Supported
Relative Advantage	Intention for BDA Implementation	0.041	11.265	0.000	61.7%	Supported
Technology Competence	Intention for BDA Implementation	0.027	4.088	0.000	63.5%	Supported

6.6 Chapter Summary

In this section, the questionnaire results are used to evaluate and ultimately implement the measuring Model. The factors that potentially affect industries' decisions to adopt BDA have been studied using the Diffusion of Innovation (DOI) and Technology, Organization, and Environment (TOE) theories. A structural model was developed from the measurement model, which established the underlying link between all constructs. The indicated items were found to be dependable as all structures and things were found to be within the appropriate ranges. When testing hypotheses, the beta coefficient is used to explain the significance level of each independent variable. The path coefficient is positive, and the P value is within the acceptable range ($P<0.005$), hence the empirical results are consistent with the provided hypotheses. The findings, limitations, and suggestions are discussed in the next chapter.

CHAPTER 7

CONCLUSIONS AND FUTURE SCOPE WORK

The following is the structure of this chapter: The “Introduction” section explains how manufacturers might benefit from big data. The results of these syntheses are discussed in the “Synthesis of Research Findings” section. The study's final results are reported in the “Conclusions and Discussion” section. In the “Contributions of Study” section, discuss the various ways in which the research has advanced the field. There are managerial ramifications provided in the “Managerial Implications” section. The section under “Research Limitations and Future Scope” section presents research limitations and future scope. Finally, the conclusion of this chapter is provided in “Concluding Remarks” section.

7.1 Introduction

The manufacturing industry has several challenges and is under significant pressure to adopt new technologies in this age of digitalization and contemporary production processes. For India's manufacturing sector to thrive, it is crucial to evaluate big data analytics (BDA) practices, vital success factors, benefits, and challenges to implementation. The effects of BDA on manufacturing activities require further research and analysis. The field of business dynamics analysis (BDA) in India's manufacturing sector has not received the attention it deserves from academics, leading to a dearth of relevant research. This research examines BDA applications in the Indian manufacturing sector, including critical success factors for BDA, benefits of BDA, and barriers to BDA.

This study's first chapter provides a general overview of BDA and its historical setting within the Indian manufacturing industry. Benefits, critical success factors, barriers, implementing BDA, research gaps, and research objectives are all discussed in the second chapter's overview of BDA in manufacturing literature. Methodology is covered in detail in the third chapter.

Analysis of barriers to implementing BDA in India's manufacturing sector is provided in the fourth chapter. The fifth chapter provides modeling of critical success factors for big data analytics implementation. The conceptual research framework, comprising hypothesis testing and modelling using SEM for statistical analysis and interpretation, is presented in Chapter 6. There are certain recommendations made in the final chapter based on all that has been analysed and researched. For the benefit of future scholars, concrete suggestions are also provided. All the major caveats of this study are discussed in this section. The study points the way for future researchers based on these limitations.

7.2 Synthesis of Research Findings

The research aims to identify the benefits, barriers, and critical success factors affecting BDA implementation. The present study combines theoretical and empirical approaches Figure 7.1 shows the results of the synthesis efforts.

In order to highlight research objectives and identify research gaps, a comprehensive literature analysis was conducted to establish current research subjects and their applicability to Indian manufacturing. In the literature review, BDA is introduced on a broad scale. The following is a synopsis of the study:

- The rapid expansion of digitalization inspired us to conduct the present study. Financial backing in BDA is a good idea. The research on BDA investment in production was scant. As a result, this served as a catalyst for investigating the state of the art in this field of study. The goals of the research are determined by the information vacuums that need to be filled.
- The context of this study has been established through a thorough literature review. Chapter 2 provides an in-depth literature evaluation of the benefits, applications, barriers, and critical success factors (CSFs) associated with BDA investment in manufacturing.

- The MCDM methodology was used to justify the implementation of BDA application, rank critical success factors, and analyze the cause and effect of critical success factors for BDA adoption in manufacturing.
- At first, the AHP method is utilized to justify the application of BDA in the Indian Manufacturing Sector. Since the study's overarching goal is to adopt BDA, establishing its value in the Indian manufacturing sector is crucial.
- The DEMATEL technique was used to determine the source and impact of the 17 most important and associated barriers to the implementation of BDA that have been discovered from the literature. In addition, Fuzzy TOPSIS was used for the ranking of the barriers.
- Critical success factors and barriers were identified based on literature and interviews with manufacturing industry experts. Fifteen critical success factors for adopting BDA for the manufacturing sector were finalized.
- These critical success factors included the Development of contract agreement among all stakeholders, Commitment and engagement of top management, Development of capability for handling big data, Robust cyber security system, Coordination among big data stakeholders, Problems identification and solving abilities, Process Integration, and institutionalization, Flexible digital infrastructure, Strategy development for BDA, Availability of quality and reliable big data, Knowledgeable and capable decision-makers, Data-driven organization culture, Process monitoring, and control, Integrating customer's requirements with performance framework and Responsive information sharing framework.

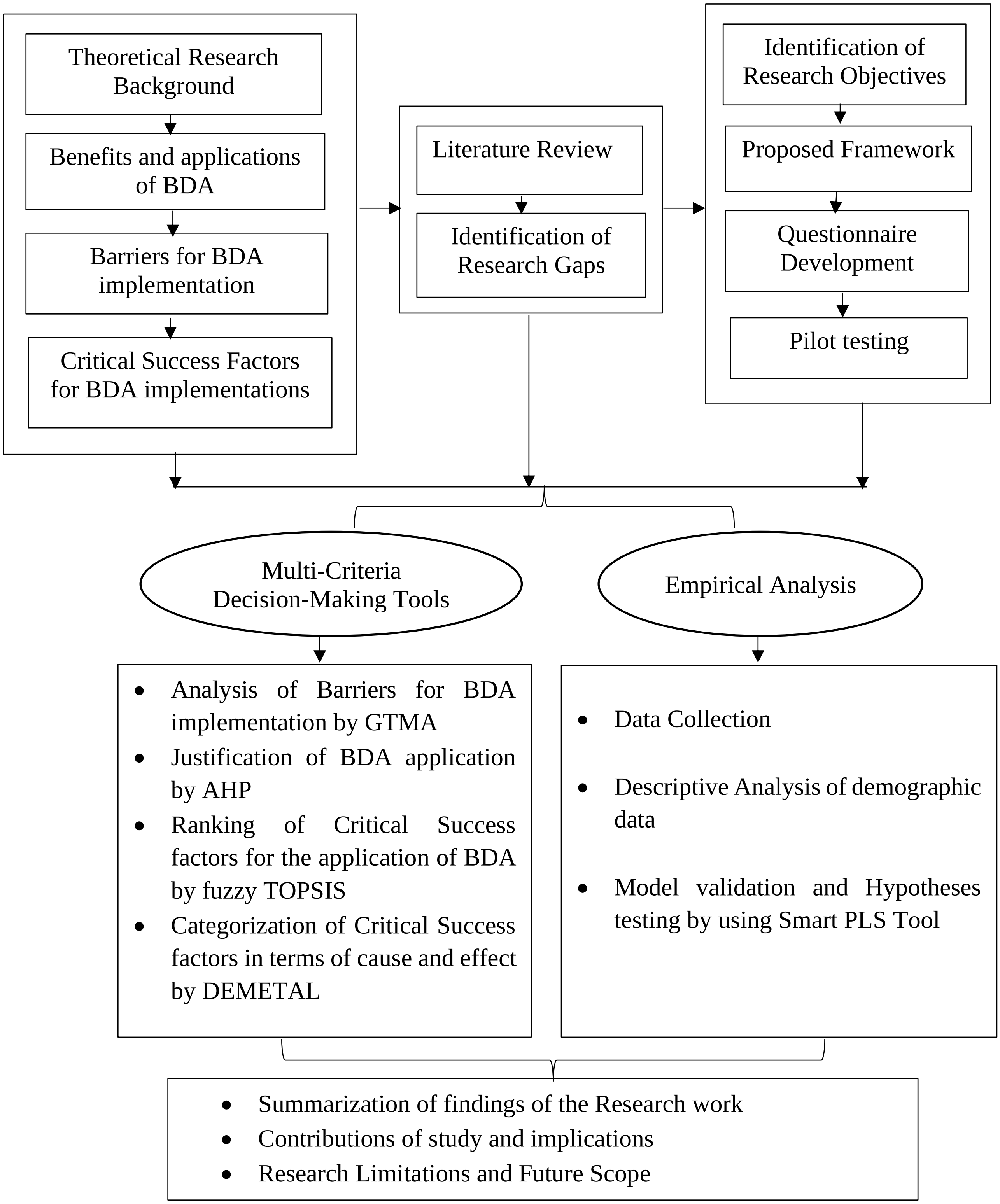

Figure 7.1 Syntheses of Research Work (Source: Self)

- A questionnaire, informed by the literature and subject-matter experts, was developed. In addition, reliable statistical methods and techniques were used to verify the accuracy of this questionnaire. Respondents working in the Indian manufacturing sector were surveyed for this study. Professionals in their fields filled out the surveys. Analyzed the BDA barriers and ranked them descriptively using SPSS 25.0 (Statistical Package for the Social Sciences) software.

- Diffusion of innovation (DOI) and the technology-organization-environment (TOE) theory were used to investigate the various factors that could influence the intention of BDA implementation in organizations. Accordingly, the hypotheses were developed and checked their significance.

7.3 Conclusions and Discussion

The conclusion of the study is presented below as per the objectives of this thesis:

1. ***Identification and Justification for benefits of BDA applications in the context of the Indian Manufacturing Industry***

The benefits of implementing BDA were justified in the context of the Indian manufacturing sector. Big data enabled manufacturing and without BDA manufacturing were the two alternatives chosen. When deciding between the two options, the seven primary benefits were weighed. Using the AHP method, we compared the Global desirability index (GDI) of the two choices and found that manufacturing with big data enabled had a GDI of 0.8811, significantly higher than the GDI value of 0.1189 for manufacturing without big data enabled. A higher value of Global desirability index justifies the BDA application for manufacturing industry.

2. ***Identification and Analysis of major barriers obstructing the implementation of BDA and develop framework for evaluating the barriers intensity index***

The barriers obstruct the implementation of BDA in the manufacturing industry, so it becomes highly crucial to identify and analyze the barriers. The analysis will help to understand the factors which act as obstructions towards BDA adoption. The various barriers were identified through the exhaustive literature review.

These barriers were ranked the from the most important to least important. The most critical barrier to invest in BDA was the lack of support from employees for implementing modern technologies. Most important barriers were High costs associated with integrating data across the supply chain, High cost of training programs on BDA, Lack of trust and commitment among employee's, Inadequate data sharing policy among stakeholders, High cost of hiring skilled BDA consultants. Less important barriers were the Lack of policies for data security and privacy data security and privacy policies and the lack of research on applications of BDA tools for manufacturing operations, which are low hurdles to investment in BDA. Further, based on factor loading, the barriers are grouped into three categories, i.e., organizational barriers, data management barriers, and human barriers. Additional to this, intensity index for each category of barriers were evaluated index using Graph theory Matrix Approach. Permanent matrices for these categories of barriers are constructed on a 1–10 scale (1 for very low and 10 for very high). To evaluate the permanent matrix index of organizational barriers, required inputs received from experts for absolute and relative values of barriers. It was observed that the organizational barriers have the highest (210684578) intensity. The data management barrier category has the second highest index (6264473) value and influences investment in BDA, whereas the human barriers have the smallest (21854) intensity. It means organization play an important role in adopting BDA.

3. Identification and ranking of Critical Success Factors in BDA implementation

Critical Success Factors are the attributes required to ensure overall success for an organization. Based on comprehensive and exhaustive literature review 15 Critical Success Factors were selected for their ranking. In order to determine a top ten list of Critical Success Factors, the Fuzzy TOPSIS method is used. In the context of BDA applications in the Indian industrial sector, a questionnaire study was carried out.

The experts were selected from industry and academia. The experts from industries and academia were requested to respond to the questionnaire designed for this study. The expert team comprises two production managers, one marketing manager, one operation engineer, one logistics manager, and two academicians.

The experts form industries have been working in their field for over 10 years, while the academic experts have been in the field for over fifteen years. Seven experts were requested to provide their responses for a rating of all 15 Critical Success Factors in linguistic terms. For this reason, a 5-point scale was employed, with the labels very low (VL), low (L), medium (M), high (H), and very high (VH) serving as the descriptors. All of the linguists' opinions were compiled and then translated to numerical values using a scale. Commitment and engagement of top management, strategy development for BDA, and development of capability for handling big data are prioritized as 1st, 2nd, and 3rd in their relative importance, which is crucial for BDA implementation.

Responsive information sharing framework and development of contract agreement among all stakeholders are ranked 14thand 15th, respectively and these factors have relatively less impact on the implementation of BDA.

Additionally, the cause and impact of crucial success elements was analysed using the DEMATEL tool. Eight Critical Success Factors in the cause group are selected based on a positive score of (SR - SC), which have an indirect effect on other Critical Success Factors in the effect group. In order to successfully implement BDA in the manufacturing sector, more focus must be given to these crucial success elements. Additional to this, based on the negative (S_R - S_C) values seven critical success factors fall in the effect group. There effect group factors are: Robust cybersecurity system, Coordination among big data stakeholders, Process integration and institutionalization, Flexible digital infrastructure, Data-driven organization culture, Process monitoring and control, and Responsive information sharing framework. These critical success factors were affected by the other critical success factors.

4. ***Exploring the determinants and developing a conceptual framework for adopting BDA in the context of Indian Manufacturing***

The Technology-Organization-Environment (TOE) and Diffusion of Innovation (DOI) theory have been employed to investigate the various factors that could influence the intention of BDA implementation in organizations. The measurement model was converted into a structural model using structural equation modeling, and the structural relationship among all constructs of BDA adoption was established.

Table 7.1 Results of Hypotheses Testing BDA Adoption constructs

		Standardize Estimate	Standard Error	T Statistics	P Values	Remark
CP	BDAI	0.086	0.034	2.513	0.014	Supported
GR	BDAI	0.424	0.043	9.919	0.000	Supported
BDAI	OF	0.354	0.054	6.556	0.000	Supported
OF	DMC	0.935	0.006	16.355	0.000	Supported
OF	FP	0.292	0.062	4.676	0.000	Supported
OF	CR	0.574	0.04	14.428	0.000	Supported
OF	SOP	0.427	0.051	8.381	0.000	Supported
OR	BDAI	0.107	0.036	2.956	0.004	Supported
RA	BDAI	0.464	0.041	11.265	0.000	Supported
TC	BDAI	0.112	0.027	4.088	0.000	Supported

The various hypotheses were analysed using SEM in smart PLS. All the path coefficients are positive, and the P value are in the acceptance range ($P<0.005$) that supported the hypotheses and Table 7.1 presented the results of the hypotheses testing.

7.4 Contributions of Study

The research work comprises the fulfillment of various objectives identified based on the research gap. The achievement of the research objectives can assist managers and top management in implementing new technologies. The current study has a strong foundation in the literature. As similar studies are limited in the Indian context, the framework in this study is developed with the help of Indian experts. Therefore, the framework results are statistically valid and can be generalized to all Indian manufacturing industries.

A comprehensive literature review has been carried out to identify barriers and critical success factors for BDA implementation that can serve as an adequate base for other researchers. A thorough literature review is conducted to identify research gaps, and subsequent research is done to fill these research gaps. Researchers and practitioners can utilize these gaps for future research in this area.

The era of digitalization offers immense opportunities for manufacturing industries to adopt new technologies. The upcoming opportunities in manufacturing will enhance operational performance and improve their decision-making capabilities. This contributes to the present study being more relevant and beneficial.

7.5 Managerial Implications

- The research contributes significantly to developing the gap related to limited studies available in Indian manufacturing industries. With the development of digitalization, manufacturing organizations are moving toward the BDA application but facing many challenges. Therefore, this study has several implications for implementing big data analytics in the manufacturing sector.

- The study suggested tools for big data analytic managers and top management, and they are expected to use them to continuously measure and monitor their scores in the different broad areas. Further, the respective Application of big data analytics, Benefits of big data analytics, Barriers, and rankings of the critical success factors could be used while adopting the various modern technologies (BDA, Industry 4.0, IoT, Cloud Computing, Artificial Intelligence, etc.) in the manufacturing industry.
- The analyses and consequences of the BDA on social, economic, and environmental performance are equally visible and understandable within the manufacturing sector. In-house comparisons could benefit from this as well. With the support of BDA, management is able to make more informed choices.
- The structural model was examined using SMART PLS software to explore the hypothesized conceptual research model. The study has taken the constructs and items of technological, organizational, and environmental contexts. This would motivate the top management of the Manufacturing Industry to implement new technology within organizations.

7.6 Research Limitations and Future Scope

There are benefits and limitations to every piece of research done. There are obviously caveats to this study. In this section, we discuss the limitations of the study and outline potential future scope.

- The major limitation of the study is that the entire research is focused on the Indian manufacturing sector. Therefore, there is a limited scope of generalization of findings for other countries and sectors.
- Various approaches like MCDM techniques and empirical analysis have been applied for data analysis of selected critical success factors and barriers to BDA

implementation. The research work may be further extended for other factors and barriers.

- The justification for applying BDA implementation in manufacturing is based on the inputs taken from seven experts. More experts from the different domains can be included in the study to generalize the results in the Indian context.
- Hypotheses are developed and tested to understand the association of independent constructs with dependent constructs. More issues related to sustainable manufacturing operations can be added to the study.

7.7 Concluding Remarks

The research work reported in the thesis may be considered an attempt to address different issues of BDA implementation in manufacturing. The research work was carried out in context to the Indian manufacturing sector. The objectives achieved in the study can assist researchers and practitioners in understanding the application and barriers of BDA in manufacturing -operations. The significant contribution and implications are also enumerated in the thesis. The present study's limitations and future scope of research have been mentioned. This study is expected to benefit manufacturing organizations, academicians, and researchers in terms of understanding, adopting, and implementing the learning based on the study's outcomes.

REFERENCES

Aboelmaged, M. G. (2014). Predicting e-readiness at firm-level: An analysis of technological, organizational, and environmental (TOE) effects on e-maintenance readiness in manufacturing firms. International Journal of Information Management, 34(5), 639-651.

Acioli, C., Scavarda, A., & Reis, A. (2021). Applying Industry 4.0 technologies in the COVID-19 sustainable chains. International Journal of Productivity and Performance Management, Vol. 70 No. 5

Adobor, H., and R. S. McMullen. (2018). "Supply Chain Resilience: A Dynamic and Multidimensional Approach." The International Journal of Logistics Management 29 (4): 1451–1471.

Agrawal, K. (2015). Investigating the determinants of Big Data Analytics (BDA) adoption in Asian emerging economies.

Agrawal, S., Singh, R.K. and Murtaza Q (2016), "Prioritizing critical success factors for reverse logistics implementation using fuzzy-TOPSIS methodology". Journal of Industrial Engineering 12:15–27.

Agrawal, S., Singh, R.K. and Murtaza, Q. (2016a), "Outsourcing decisions in reverse logistics: sustainable balanced scorecard and graph theoretic approach", Resources, Conservation and Recycling, Vol. 108, pp. 41-53.

Ahmed, E., Yaqoob, I., Hashem, I. A. T., Khan, I., Ahmed, A. I. A., Imran, M., & Vasilakos, A. V. (2017). The role of big data analytics in Internet of Things. Computer Networks, 129, 459-471.

Ahmed, V., Aziz, Z., Tezel, A. and Riaz, Z. (2018), "Challenges and drivers for data mining in the AEC sector", Engineering, Construction and Architectural Management, Emerald Publishing, Vol. 25 No. 11, pp. 1436-1453.

Aho, A.-M. (2015), "Product data analytics service model for manufacturing company", International Conference on Knowledge Management in Organizations, pp. 282-296

AI-Barashdi, H., & AI-Karousi, R. (2019). Big Data in academic libraries: literature review and future research directions. Journal of Information Studies & Technology (JIS&T), 2018(2), 13.

Akhtar, P., Frynas, J.G., Mellahi, K. and Ullah, S. (2019), "Big data-savvy teams' skills, big data-driven actions, and business performance", British Journal of Management, Vol. 30 No. 2, pp. 252-271.

Akter, S., Wamba, S. F., Gunasekaran, A., Dubey, R., & Childe, S. J. (2016). How to improve firm performance using big data analytics capability and business strategy alignment. International Journal of Production Economics, 182, 113-131.

Alalawneh, A. A., & Alkhatib, S. F. (2021). The barriers to big data adoption in developing economies. The Electronic Journal of Information Systems in Developing Countries, 87(1), e12151.

Albar, A. M., and Hoque, M. R. (2019). Factors affecting cloud ERP adoption in Saudi Arabia: An empirical study. Information Development, 35(1), 150-164.

Alfaro, L.A., Le, T.M.H., Choi, H.R., and Cho, M.J. (2015), "Deployment model of Big Data for port logistics", International Information Institute (Tokyo), Vol. 18 No. 1, p. 7.

Alharthi, A., Krotov, V. and Bowman, M. (2017), "Addressing barriers to big data", Business Horizons, Vol. 60 No. 3, pp. 285-292.

Ali, I. and Golgeci, I. (2019), "Where is supply chain resilience research heading? A systematic and co-occurrence analysis," International Journal of Physical Distribution and Logistics Management, Vol. 49 No. 8, pp. 793-815.

Alsaad, A., Mohamad, R., and Ismail, N. (2017). The Moderating Role of Trust in Business-to-Business Electronic Commerce (B2B Ec) Adoption. Computers in Human Behavior, 68(1), 157–169.

Alsghaier, H., Akour, M., Shehabat, I. and Aldiabat, S. (2017), "The importance of big data analytics in business: a case study", American Journal of Software Engineering and Applications, Vol. 6 No. 4, pp. 111-115.

Alshamaila, Y., Papagiannidis, S., & Li, F. (2013). Cloud computing adoption by SMEs in the north-east of England: A multi-perspective framework. Journal of Enterprise Information Management, 26(3), 250-275.

Altuntas, S., & Dereli, T. (2015). A novel approach based on DEMATEL method and patent citation analysis for prioritizing a portfolio of investment projects. Expert systems with Applications, 42(3), 1003-1012.

Amerioun, A., Alidadi, A., Zaboli, R. and Sepandi, M. (2018), "The data on exploratory factor analysis of factors influencing employee's effectiveness for responding to crisis in Iran military hospitals", Data in Brief, Vol. 19, pp. 1522-1529

Amui LBL, Jabbour CJC, de Sousa Jabbour ABL, Kannan D (2017) Sustainability as a dynamic organizational capability: a systematic review and a future agenda toward a sustainable transition. Journal of Cleaner Production 142:308–322.

Ardito, L., Petruzzelli, A.M., Panniello, U. and Garavelli, A.C. (2019), "Towards industry 4.0", Business Process Management Journal, Vol. 25 No. 2, pp. 323-346

Arunachalam, D., Kumar, N. and Kawalek, J.P. (2018), "Understanding big data analytics capabilities in supply chain management: unravelling the issues, challenges and implications for practice", Transportation Research Part E: Logistics and Transportation Review, Vol. 114, pp. 416-436.

Auschitzky, E., Hammer, M., & Rajagopaul, A. (2014). How big data can improve manufacturing. McKinsey & Company.

Awa, H.O., Ojiabo, U. and Emecheta, B., C. (2015), "Integrating TAM, TPB and TOE frameworks and expanding their characteristic constructs for e-commerce adoption by SMEs", Journal of Science and Technology Policy Management, Vol. 6 No. 1, pp. 76-94.

Aydiner, A.S., Tatoglu, E., Bayraktar, E., Zaim, S. and Delen, D. (2019), "Business analytics and firm performance: the mediating role of business process performance", Journal of Business Research, Elsevier, Vol. 96, pp. 228-237.

Ayed, A. B., Halima, M. B., & Alimi, A. M. (2015). Big data analytics for logistics and transportation. In 2015 4th International Conference on Advanced Logistics and Transport (pp. 311-316). IEEE.

Bag S, Wood LC, Xu L et al; (2020) Big data analytics as an operational excellence approach to enhance sustainable supply chain performance. Resources, Conservation and Recycling, 153:104559.

Bag, S. (2017). Big data and predictive analysis is key to superior supply chain performance: a South African experience. International Journal of Information Systems and Supply Chain Management, 10(2), 66-84.

Bag, S., Gupta, S., Foropon, C., (2018a). Examining the role of dynamic remanufacturing capability and supply chain resilience in the circular economy. Manag. Decis. 57 (4),863–885.

Bag, S., Wood, L. C., Xu, L., Dhamija, P., & Kayikci, Y. (2020). Big data analytics as an operational excellence approach to enhance sustainable supply chain performance. Resources, Conservation and Recycling, 153, 104559.

Baldwin, H. (2015), "When Big Data projects go wrong", Forbes, available at: http://www.forbes.com/sites/howardbaldwin/2015/01/22/when-big-data-projects-go-wrong/#78ae288a623

Banyai, T., Tamas, P., Illes, B., Stankeviciute, Z. and Banyai, A. (2019), _ "Optimization of municipal waste collection routing: impact of industry 4.0 technologies on environmental awareness and sustainability", International Journal of Environmental Research and Public Health, Vol. 16 No. 4, p. 634

Barbierato, E., Gribaudo, M. and Iacono, M. (2014), "Performance evaluation of NoSQL big-data applications using multi-formalism models", Future Generation Computer Systems, Elsevier, Vol. 37, pp. 345-353

Barlow M (2013) Real-time big data analytics: emerging architecture. O'Reilly Media, Sebastopol, USA

Barton, D., & Court, D. (2012). Making advanced analytics work for you. Harvard Business Review, 90(10), 78-83.

Barzegar, M., Ehtesham Rasi, R.N and Niknamfar, A.H. (2018), "Analyzing the drivers of green manufacturing using an analytic network process method: a case study", International Journal of Research in Industrial Engineering, Vol. 7 No. 1, pp. 61-83

Beath, C., Becerra-Fernandez, I., Ross, J. and Short, J. (2012), "Finding value in the information explosion", MIT Sloan Management Review, Vol. 53 No. 4, p. 18

Belaud, J.-P., Prioux, N., Vialle, C. and Sablayrolles, C. (2019), "Big data for agri-food 4.0: application to sustainability management for by-products supply chain", Computers in Industry, Vol. 111, pp. 41-50

Belhadi, A., Kamble, S. S., Zkik, K., Cherrafi, A., & Touriki, F. E. (2020). The integrated effect of Big Data Analytics, Lean Six Sigma and Green Manufacturing on the environmental performance of manufacturing companies: The case of North Africa. Journal of Cleaner Production, 252, 119903.

Belhadi, A., Zkik, K., Cherrafi, A., & Sha'ri, M. Y. (2019). Understanding big data analytics for manufacturing processes: insights from literature review and multiple case studies. Computers & Industrial Engineering, 137, 106099.

Bhandari, D., Singh, R.K. and Garg, S.K. (2019), "Prioritisation and evaluation of barriers intensity for implementation of cleaner technologies: framework for sustainable production", Resources, Conservation and Recycling, Vol. 146, pp. 156-167.

Bharadwaj, A. S. (2000). A resource-based perspective on information technology capability and firm performance: An empirical investigation. MIS Quarterly, 24(1), 169–196.

Bi and Cochran, D. (2014). Big data analytics with applications. Journal of Management Analytics, 1(4), 249-265.

Biesdorf, S., Court, D., & Willmott, P. (2013). Big data: What’s your plan? McKinsey Quarterly, March (2), 40-51.

Big data framework.org/short-history-of-big-data (2019)/ Accessed on March2022

Birkel, H., Veile, J., Muller, J., Hartmann, E. and Voigt, K.-I. (2019), "Development of a risk framework for industry 4.0 in the context of sustainability for established manufacturers", Sustainability, Vol. 11 No. 2, p. 384

Biswas, S., and Sen, J. (2016). A proposed framework of next generation supply chain management using big data analytics. In Proceedings of National Conference on Emerging Trends in Business and Management: Issues and Challenges. Kolkata: India.

Boyd, D., & Crawford, K. (2012). Critical questions for big data: Provocations for a cultural, technological, and scholarly phenomenon. Information, communication & society, 15(5), 662-679.

Braganza, A., Brooks, L., Nepelski, D., Ali, M., & Moro, R. (2017). Resource management in big data initiatives: Processes and dynamic capabilities. Journal of Business Research, 70, 328-337.

Brandon-Jones, E., B. Squire, C. W. Autry, and K. J. Petersen (2014). "A Contingent Resource-Based Perspective of Supply Chain Resilience and Robustness." Journal of Supply Chain Management 50 (3): 55–73.

Brinch, M., Stentoft, J., & Jensen, J. K. (2017). Big data and its applications in supply chain management: Findings from a Delphi study. In Proceedings of the 50th Hawaii International Conference on System Sciences

Brouer, B. D., Karsten, C. V., & Pisinger, D. (2016). Big data optimization in maritime logistics. In A. Emrouznejad (Ed.), Big data optimization: Recent developments and challenges (pp. 319-344). Cham: Springer.

Bujang, M. A., Omar, E. D., & Baharum, N. A. (2018). A review on sample size determination for Cronbach's alpha test: a simple guide for researchers. The Malaysian journal of medical sciences: MJMS, 25(6), 85.

Buntak, K., Kovacic, M. and Mutavdzija, M. (2019), "Internet of things and smart warehouses as the future of logistics", Tehnicki Glasnik, Vol. 13 No. 3, pp. 248-253

Chae, B. K., Yang, C., Olson, D., & Sheu, C. (2014). The impact of advanced analytics and data accuracy on operational performance: A contingent resource-based theory (RBT) perspective. Decision Support Systems, 59, 119-126.

Chains." International Journal of Production Economics, 203, 379-393.

Chase Jr, C. W. (2013). Using big data to enhance demand-driven forecasting and planning. The Journal of Business Forecasting, 32(2), 27-32.

Chen M, Mao S, Liu Y (2014) Big data: a survey. Mob Networks Appl 19:171–209. https://doi.org/10.1007/s11036-013-0489-0

Chen, D. Q., Preston, D. S., & Swink, M. (2015). How the use of big data analytics affects value creation in supply chain management. Journal of Management Information Systems, 32(4), 4-39.

Chen, D. Q., Preston, D. S., & Swink, M. (2015). How the use of big data analytics affects value creation in supply chain management. Journal of management information systems, 32(4), 4-39.

Chen, H., Chiang, R. H., & Storey, V. C. (2012). Business intelligence and analytics: From big data to big impact. MIS Quarterly, 36(4), 1165-1188.

Choi, T.-M., Wallace, S.W. and Wang, Y. (2018), "Big data analytics in operations management", Production and Operations Management, Wiley Online Library, Vol. 27 No. 10, pp. 1868-1883

Chowdhury, M. M. H., and M. Quaddus. (2017). "Supply Chain Resilience: Conceptualization and Scale Development Using Dynamic Capability Theory." International Journal of Production Economics 188: 185–204.

Christina, O.C. and Stephen, K. (2017), "Facilitating knowledge management through filtered big data: SME competitiveness in an agri-food sector", Journal of Knowledge Management, Vol. 21, pp. 156-179.

Constantiou, I. D., & Kallinikos, J. (2015). New games, new rules: big data and the changing context of strategy. Journal of Information Technology, 30(1), 44-57.

Cui, Y., Kara, S., & Chan, K. C. (2020). Manufacturing big data ecosystem: A systematic literature review. Robotics and computer-integrated Manufacturing, 62, 101861.

Das R, Shaw K, Irfan M (2020) Supply chain network design considering carbon footprint, water footprint, supplier's social risk, solid waste, and service level under the uncertain condition. Clean Technol Environ Policy 22:337–370

De Camargo FP, Roman Pais Seles BM, Chiappetta Jabbour CJ et al. (2018) Management theory and big data literature: from a review to a research agenda. International Journal of Information Management, 43:112–129.

De Coster, J. (1998), Overview of Factor Analysis, Tuscaloosa, AL.

De Oliveira, M. P. V., McCormack, K., & Trkman, P. (2012). Business analytics in supply chains- The contingent effect of business process maturity. Expert Systems with Applications, 39(5), 5488-5498.

Del Fabbro E, Santarossa D (2016) Ergonomic Analysis in Manufacturing Process A real time approach. Procedia CIRP 41:957–962.

Delen, D. and Ram, S. (2018), "Research challenges and opportunities in business analytics", Journal of Business Analytics, Taylor & Francis, Vol. 1 No. 1, pp. 2-12

Demirkan, H., & Delen, D. (2013). Leveraging the capabilities of service-oriented decision support systems: Putting analytics and big data in cloud. Decision Support Systems, 55(1), 412-421.

Diaz, A., Rowshankish, K. and Saleh, T. (2018), "Why data culture matters", McKinsey Quarterly, Vol. 3, pp. 36-53.

Ding, B. (2018), "Pharma industry 4.0: literature review and research opportunities in sustainable pharmaceutical supply chains", Process Safety and Environmental Protection, Vol. 119, pp. 115-130

Donoho, D., (2015). 50 years of Data Science. URL http://courses. csail. mit. edu/18, 337.

Doolun, I. S., Ponnambalam, S. G., Subramanian, N., & Kanagaraj, G. (2018). Data driven hybrid evolutionary analytical approach for multi objective location allocation decisions: Automotive green supply chain empirical evidence. Computers & Operations Research, 98, 265-283.

Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2019). Artificial intelligence for decision making in the era of Big Data–evolution, challenges and research agenda. International journal of information management, 48, 63-71.

Dubey R, Gunasekaran A, Childe SJ et al (2019) Big data analytics and organizational culture as complements to swift trust and collaborative performance in the humanitarian supply chain. Int J Prod Econ 210:120–136.

Dubey, R., Gunasekaran, A., Childe, S. J., Fosso Wamba, S., Roubaud, D., & Foropon, C. (2021). Empirical investigation of data analytics capability and organizational flexibility as complements to supply chain resilience. International Journal of Production Research, 59(1), 110-128.

Dubey, R., Gunasekaran, A., Childe, S. J., Wamba, S. F., & Papadopoulos, T. (2016). The impact of big data on world-class sustainable manufacturing. The International Journal of Advanced Manufacturing Technology, 84(1-4), 631-645.

Dubey, R., Gunasekaran, A., Childe, S.J., Bryde, D.J., Giannakis, M., Foropon, C., Roubaud, D. and Hazen, B.T. (2020), "Big data analytics and artificial intelligence pathway to operational performance under the effects of entrepreneurial orientation and environmental dynamism: a study of manufacturing organizations", International Journal of Production Economics, Vol. 226, 107599.

Ebenezer, J. G. A., & Durga, S. (2015). Big data analytics in healthcare: A survey. Journal of Engineering & Applied Sciences, 10(8), 3645-3650.

Eisenhardt, K.M., Graebner, M.E. and Sonenshein, S. (2016), "Grand challenges and inductive methods: rigor without rigor mortis", Academy of Management Journal, Vol. 59 No. 4, pp.1113-1123.

Elgendy N, Elragal A (2014) Big data analytics: a literature review paper. pp 214–227

ElMaraghy, H. A., Youssef, A. M., Marzouk, A. M., & ElMaraghy, W. H. (2017). Energy use analysis and local benchmarking of manufacturing lines. Journal of cleaner production, 163, 36-48.

EPU (2017), "Chapter 3: Five strategic thrusts and national-level initiatives", Malaysia Productivity Blueprint, Economic Planning Unit.

Esteves, J., and Curto, J. (2013). A risk and benefits behavioral model to assess intentions to adopt big data. Journal of Intelligence Studies in Business, 3(1), 37–46.

Fercoq, A., Lamouri, S., & Carbone, V. (2016). Lean/Green integration focused on waste reduction techniques. Journal of Cleaner production, 137, 567-578.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39-50.

Fosso Wamba, S., Gunasekaran, A., Bhattacharya, M., & Dubey, R. (2016). Determinants of RFID adoption intention by SMEs: An empirical investigation. Production Planning & Control, 27(12), 979-990.

Frehe, V., Kleinschmidt, T., & Teuteberg, F. (2014). Big data in logistics-Identifying potentials through literature, case study and expert interview analyses. In GI-Jahrestagung (pp. 173-186).

Frizzo-Barker, J., Chow-White, P.A., Mozafari, M. and Ha, D. (2016), "An empirical study of the rise of big data in business scholarship", International Journal of Information Management, Elsevier, Vol. 36 No. 3, pp. 403-413.

Gabriel, M. and Pessel, E. (2016), "Industry 4.0 and sustainability impacts: critical discussion of sustainability aspects with a special focus on future of work and ecological consequences", International Journal of Engineering, Vol. 14 No. 2, pp. 131-136.

Gandhi, S., Mangla, S. K., Kumar, P., & Kumar, D. (2015). Evaluating factors in implementation of successful green supply chain management using DEMATEL: A case study. International strategic management review, 3(1-2), 96-109.

Gandomi A. and Haider M. (2015) Beyond the hype: Big data concepts, methods, and analytics, International Journal of Information Management, 35(2), 137-144.

Ganeshan, R., & Sanders, N. (2018). How big data could challenge planning processes across the supply chain. Foresight: The International Journal of Applied Forecasting, (50), 19-24.

Gaskin, C. J., & Happell, B. (2014). On exploratory factor analysis: A review of recent evidence, an assessment of current practice, and recommendations for future use. International journal of nursing studies, 51(3), 511-521.

Gawankar, S. A., Gunasekaran, A., & Kamble, S. (2020). A study on investments in the big data-driven supply chain, performance measures and organisational performance in Indian retail 4.0 context. International Journal of Production Research, 58(5), 1574-1593.

George, G., Haas, M. R., & Pentland, A. (2014). Big data and management. Academy of management Journal, 57(2), 321-326.

George, G., Howard-Grenville, J., Joshi, A. and Tihanyi, L. (2016), "Understanding and tackling societal grand challenges through management research", Academy of Management Journal, Vol. 59 No. 6, pp. 1880-1895

Ghadge, A., Er Kara, M., Moradlou, H. and Goswami, M. (2020), "The impact of Industry 4.0 implementation on supply chains", Journal of Manufacturing Technology Management, Emerald Publishing, Vol. 31 No. 4, pp. 669-686

Ghasemaghaei, M. and Calic, G. (2019), "Does big data enhance firm innovation competency? The mediating role of data-driven insights," Journal of Business Research, Elsevier, Vol. 104, pp. 69-84

Ghobakhloo, M., Hong, T.S., Sabouri, M.S. and Zulkifli, N. (2012), "Strategies for Success information technology adoption in small and medium-sized enterprises", Information, Vol. 3 No. 1, 36-67.

Giannakis, M. and Louis, M. (2016), "A multi-agent-based system with big data processing for enhanced supply chain agility", Journal of Enterprise Information Management, Emerald Group Publishing, Vol. 29 No. 5, pp. 706-727.

Gill, N.S. (2021), "10 latest trends in Big Data analytics that you should know in 2021", available at: https://www.xenonstack.com/blog/latest-trends-in-big-data-analytics

Gong M, Simpson A, Koh L, Tan KH (2018) Inside out: The interrelationships of sustainable performance metrics and its effect on business decision making: Theory and practice. Resour Conserv Recycl 128:155–166.

Govindarajulu, N. and Daily, B.F. (2004), "Motivating employees for environmental improvement", Industrial Management and Data Systems, Emerald Group Publishing, Vol. 104 No. 4, pp. 364-372.

Grover, S., Agrawal, V.P., and Khan, I.A. (2006), "Role of human factors in TQM: a graph theoretic approach", Benchmarking: An International Journal, Vol. 13 No. 4, pp. 447-468

Gudfinnsson, K., Strand, M., & Berndtsson, M. (2015). Analysing business intelligence maturity. Journal of Decision Systems, 24(1), 37-54.

Gunasekaran, A. and Spalanzani, A. (2012), "Sustainability of manufacturing and services: investigations for research and applications", International Journal of Production Economics, Elsevier, Vol. 140 No. 1, pp. 35-47

Gunasekaran, A., Papadopoulos, T., Dubey, R., Wamba, S. F., Childe, S. J., Hazen, B., & Akter, S. (2017). Big data and predictive analytics for supply chain and organizational performance. Journal of Business Research, 70, 308-317.

Gunasekaran, A., Subramanian, N. and Ngai, W. T. E. (2019), "Quality management in the 21st century enterprises: Research pathway towards Industry 4.0", Vol.207 No. January, pp. 125-129

Gupta S, Modgil S, Gunasekaran A (2020) Big data in lean six sigma: a review and further research directions. International Journal of Production Research 58:947–969.

Gupta S., Altay, N. and Luo, Z. (2019), "Big data in humanitarian supply chain management: a review and further research directions", Annals of Operations Research, Springer, Vol. 283 No. 1, pp. 1153-1173.

Gupta, A., Singh, R. K., & Suri, P. K. (2018). Prioritizing critical success factors for sustainable service quality management by logistics service providers. Vis J Bus Perspect 22: 295–305.

Gupta, H., and Barua, M.K. (2016), "Identifying enablers of technological innovation for Indian MSMEs using best-worst multi criteria decision making method", Technological Forecasting and Social Change, Vol. 107, pp. 69-79.

Gupta, K., Dangayach, T., Kumar, G. and Gupta, P. (2017), "Disassembly index evaluation of automotive systems using graph theory and AHP", 2017 6th International Conference on JEIM 35,1 206 Reliability, Infocom Technologies and Optimization (Trends and Future Directions) (ICRITO), Noida, India, IEEE, pp. 261-266.

Gupta, M., and George, J.F. (2016), "Toward the development of a big data analytics capability", Information and Management, Vol. 53 No. 8, pp. 1049-1064

Hair, J.F., Black, W.C., Babin, B.J. and Anderson, R.E. (2010) Multivariate Data Analysis. 7th Edition, Pearson, New York.

Hazen, B. T., Skipper, J. B., Ezell, J. D., & Boone, C. A. (2016). Big data and predictive analytics for supply chain sustainability: A theory-driven research agenda. Computers & Industrial Engineering, 101, 592-598.

Hidayanto, A. N., Abednego, N., Aminah, S., & Sucahyo, Y. G. (2015). Analysis of cloud adoption determinants by using BOCR analysis and DEMATEL. International Journal of Business Information Systems, 18(2), 221-248.

Hofmann, E., Rutschmann, E., 2018. Big data analytics and demand forecasting in supply chains: A conceptual analysis. The International Journal of Logistics Management 29, 739–766.

Hopkins, J., & Hawking, P. (2018). Big Data Analytics and IoT in logistics: a case study. International Journal of Logistics Management, 29(2), 575-591.

Iacovou, C.L., Benbasat, I. and Dexter, A.S. (1995), "Electronic data interchange and small organizations: adoption and impact of technology", MIS Quarterly, Vol. 19 No. 4, pp. 465-485.

IBM Corp. Released (2017) IBM SPSS Statistics for Windows, Version 25.0. IBM Corp., Armonk, NY.

Ifinedo, P. (2006). Acceptance and continuance intention of web-based learning technologies (WLT) use among university students in a Baltic country. The Electronic Journal of Information Systems in Developing Countries, 23(1), 1-20.

Inamdar, Z., Raut, R., Narwane, V.S., Gardas, B., Narkhede, B. and Sagnak, M. (2020), "A systematic literature review with bibliometric analysis of big data analytics adoption from period 2014 to 2018", Journal of Enterprise Information Management, Emerald Publishing.

Iqbal, M., Kazmi, S.H.A., Manzoor, A., Soomrani, A.R., Butt, S.H. and Shaikh, K.A. (2018), "A study of big data for business growth in SMEs: opportunities and challenges", International Conference on Computing, Mathematics and Engineering Technologies.

Ivanov D, Dolgui A, Sokolov B (2019) The impact of digital technology and Industry 4.0 on the ripple effect and supply chain risk analytics. International Journal of Production Research 57:829–846.

Ivanov, D., A. Dolgui, and B. Sokolov. (2018). "Scheduling of Recovery Actions in the Supply Chain with Resilience Analysis Considerations." International Journal of Production Research 56 (19): 6473–6490.

Jabbour, C.J.C., Fiorini, P.D.C., Ndubisi, N.O., Queiroz, M.M. and Piato, E.L. (2020), "Digitally enabled sustainable supply chains in the 21st century: a review and a research agenda", Science of The Total Environment, Elsevier, Vol. 725, p. 138177.

Jahanshahi, A.A. and Brem, A. (2017), "Sustainability in SMEs: top management teams behavioral integration as source of innovativeness", Sustainability, Multidisciplinary Digital Publishing Institute, Vol. 9 No. 10, p. 1899.

Janssen, M., van der Voort, H., & Wahyudi, A. (2017). Factors influencing big data decision-making quality. Journal of business research, 70, 338-345.

Jensen, J.P. and Remmen, A. (2017), "Enabling circular economy through product stewardship", Procedia Manufacturing, Vol. 8, pp. 377-384

Jeong, S. R., & Ghani, I. (2014). Semantic computing for big data: approaches, tools, and emerging directions (2011-2014). KSII Transactions on Internet and Information Systems (TIIS), 8(6), 2022-2042.

Jiang, H., Chen, Y., Qiao, Z., Weng, T.-H. and Li, K.-C. (2015), "Scaling up MapReduce-based big data processing on multi-GPU systems", Cluster Computing, Springer, Vol. 18 No. 1, pp. 369-383.

Ji-fan Ren, S., Fosso Wamba, S., Akter, S., Dubey, R., & Childe, S. J. (2017). Modelling quality dynamics, business value and firm performance in a big data analytics environment. International Journal of Production Research, 55(17), 5011-5026.

Jin, Y., & Ji, S. (2013). Partner choice of supply chain based on 3d printing and big data. Information Technology Journal, 12(22), 6822-6826.

Junge, A.L. (2019), "Digital transformation technologies as an enabler for sustainable logistics and supply chain processes an exploratory framework", Brazilian Journal of Operations and Production Management, Vol. 16 No. 3, pp. 462-472.

Junior, F. R. L., Osiro, L., & Carpinetti, L. C. R. (2014). A comparison between Fuzzy AHP and Fuzzy TOPSIS methods to supplier selection. Applied soft computing, 21, 194-209.

Kache, F. and Seuring, S. (2017), "Challenges and opportunities of digital information at the intersection of Big Data analytics and supply chain management", International Journal of Operations and Production Management, Vol. 37 No. 1, pp. 10-36.

Kaisler, S., Armour, F., Espinosa, J. A., & Money, W. (2013). Big data: Issues and challenges moving forward. In 2013 46th Hawaii International Conference on System Sciences (pp. 995-1004). IEEE.

Kalema, B.M.M., Motsi, L. and Motjolopane, I.M. (2016), "Utilizing IT to enhance knowledge sharing for school educators in developing countries", The Electronic Journal of Information Systems in Developing Countries, Wiley Online Library, Vol. 73 No. 1, pp. 1-22.

Kamble, S., Gunasekaran, A. and Dhone, N.C. (2020a), "Industry 4.0 and lean manufacturing practices for sustainable organizational performance in Indian manufacturing companies", International Journal of Production Research, Vol. 58 No. 5, pp. 1319-1337.

Kamble, S.S. and Gunasekaran, A. (2020), "Big data-driven supply chain performance measurement system: a review and framework for implementation", International Journal of Production Research, Vol. 58 No. 1, pp. 65-86.

Kamble, S.S., Gunasekaran, A., Ghadge, A. and Raut, R. (2020), "A performance measurement system for industry 4.0 enabled smart manufacturing system in SMMEs- A review and empirical investigation", International Journal of Production Economics, Elsevier, Vol. 229, p. 107853.

Katchasuwanmanee, K., Bateman, R., & Cheng, K. (2016). Development of the energy-smart production management system (e-ProMan): A big data driven approach, analysis, and optimisation. Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture, 230(5), 972-978.

Kazancoglu, Y., Ozbiltekin Pala, M., Sezer, M.D., Luthra, S. and Kumar, A. (2021), "Drivers of implementing Big Data Analytics in food supply chains for transition to a circular economy and sustainable operations management", Journal of Enterprise Information Management

Kim G, Park CS, Yoon KP (1997) Identifying investment opportunities for advanced manufacturing systems with comparative-integrated performance measurement. International Journal of Production Economics 50:23–33.

Kim, G.-H., Trimi, S. and Chung, J.-H. (2014), "Big-data applications in the government sector", Communications of the ACM, ACM New York, NY, Vol. 57 No. 3, pp. 78-85.

Kirchherr, J., Reike, D., & Hekkert, M. (2017). Conceptualizing the circular economy: An analysis of 114 definitions. Resources, conservation, and recycling, 127, 221-232.

Kuan, K. K. Y., and Chau, P. Y. K. (2001). A perception-based model for edi adoption in small businesses using a technology-organization-environment framework. Information and Management, 38(8), 507–521.

Kumar P, and Singh RK (2012) A fuzzy AHP and TOPSIS methodology to evaluate 3PL in a supply chain. J Model Manag 7:287–303.

Kumar, N., Kumar, G., and Singh, R.K. (2021), "Big data analytics application for sustainable manufacturing operations: analysis of strategic factors", Clean Technologies and Environmental Policy, Vol. 23, pp. 965-989

Kumar, P., Singh, R.K. and Kumar, R. (2017), "An integrated framework of interpretive structural modeling and graph theory matrix approach to fix the agility index of an automobile manufacturing organization", International Journal of System Assurance Engineering and Management, Vol. 8 No. S1, pp. 342-352

Kwon, O., Lee, N., & Shin, B. (2014). Data quality management, data usage experience and acquisition intention of big data analytics. International Journal of Information Management, 34(3), 387-394.

Lai, Y., Sun, H., & Ren, J. (2018). Understanding the determinants of big data analytics (BDA) adoption in logistics and supply chain management: An empirical investigation. The International Journal of Logistics Management, 29(2), 676-703.

Lamba, K., & Singh, S. P. (2017). Big data in operations and supply chain management: current trends and future perspectives. Production Planning & Control, 28(11-12), 877-890.

Laney, D. (2012). The importance of' big data': A definition. Gartner. Retrieved, 21, 2014-2018.

Laney, D., 2001. 3D data management: Controlling data volume, velocity, and variety.

LaValle, S., Lesser, E., Shockley, R., Hopkins, M. S., & Kruschwitz, N. (2011). Big data, analytics, and the path from insights to value. MIT Sloan Management Review, 52(2), 21-32.

Law, K. M., & Gunasekaran, A. (2012). Sustainability development in high-tech manufacturing firms in Hong Kong: Motivators and readiness. International Journal of Production Economics, 137(1), 116-125.

Lechler, S., Canzaniello, A., Robmann, B., von der Gracht, H.A. and Hartmann, E. (2019), "Real-time data processing in supply chain management: revealing the uncertainty dilemma", International Journal of Physical Distribution and Logistics Management, Vol. 49 No. 10, pp. 1003-1019

Lee J, Ardakani HD, Yang S, Bagheri B (2015) Industrial big data analytics and cyber-physical systems for future maintenance and service innovation. Procedia CIRP 38:3–7.

Lee, I. (2017). Big data: Dimensions, evolution, impacts, and challenges. Business horizons, 60(3), 293-303.

Li, G., Huang, D., Sun, C., & Li, Y. (2019). Developing interpretive structural modeling based on factor analysis for the water-energy-food nexus conundrum. Science of The Total Environment, 651, 309-322.

Li, Y.-H. (2008), "An empirical investigation on the determinants of e-procurement adoption in Chinese manufacturing enterprises. Management science and engineering," ICMSE 2008. 15th Annual Conference Proceedings, International Conference on, 2008, IEEE, pp. 32-37.

Lian, J. W., Yen, D. C., & Wang, Y. T. (2014). An exploratory study to understand the critical factors affecting the decision to adopt cloud computing in Taiwan hospital. International Journal of Information Management, 34(1), 28-36

Lin, K. P., Tseng, M. L., & Pai, P. F. (2018). Sustainable supply chain management using approximate fuzzy DEMATEL method. Resources, Conservation and Recycling, 128, 134-142.

Lin, R. J. (2013). Using fuzzy DEMATEL to evaluate the green supply chain management practices. Journal of cleaner production, 40, 32-39.

Liu, Y., Zhang, Y., Ren, S., Yang, M., Wang, Y. and Huisingh, D. (2020), "How can smart technologies contribute to sustainable product lifecycle management?", Journal of Cleaner Production, Vol. 249, p. 119423

Llave, M. R. (2017). Business intelligence and analytics in small and medium-sized enterprises: A systematic literature review. Procedia Computer Science, 121, 194-205.

Lohr, S., 2014. For big-data scientists, 'janitor work is key hurdle to insights. New York Times, 17

Luo, Z., Dubey, R., Gunasekaran, A., Childe, S.J., Papadopoulos, T., Hazen, B. and Roubaud, D. (2017), "Sustainable production framework for cement manufacturing firms: a behavioural perspective", Renewable and Sustainable Energy Reviews, Vol. 78, pp. 495-502

Luthra, S., Govindan, K., Kharb, R. K., & Mangla, S. K. (2016). Evaluating the enablers in solar power developments in the current scenario using fuzzy DEMATEL: An Indian perspective. Renewable and Sustainable Energy Reviews, 63, 379-397.

Machado, C.G., Winroth, M.P. and da Silva, E.H.D. (2020), "Sustainable manufacturing in Industry 4.0: an emerging research agenda", International Journal of Production Research, Taylor & Francis, Vol. 58 No. 5, pp. 1462-1484.

Maduku, D.K., Mpinganjira, M. and Duh, H. (2016), "Understanding mobile marketing adoption intention by South African SMEs: a multi-perspective framework", International Journal of Information Management, Elsevier, Vol. 36 No. 5, pp. 711-723.

Malomo, F. and Sena, V. (2017), "Data intelligence for local government? Assessing the benefits and barriers to use of big data in the public sector," Policy and Internet, Vol. 9 No. 1, pp. 7-27.

Manavalan, E., & Jayakrishna, K. (2019). A review of Internet of Things (IoT) embedded sustainable supply chain for industry 4.0 requirements. Computers & Industrial Engineering, 127, 925-953.

Mangla, S. K., Luthra, S., Rich, N., Kumar, D., & Nripendra, P. Rana, and Yogesh K. Dwivedi. (2018) "Enablers to Implement Sustainable Initiatives in Agri-Food Supply Chains." International Journal of Production Economics, 203, 379-393.

Mangla, S.K., Raut, R., Narwane, V.S., Zhang, Z.J. and Priyadarshinee, P. (2020), "Mediating effect of big data analytics on project performance of small and medium enterprises", Journal of Enterprise Information Management, Emerald Publishing,

Manyika, J., Chui, M., Brown, B., Bughin, J., Dobbs, R., Roxburgh, C. and A.H.B. (2011), Big Data: The Next Frontier for Innovation, Competition, and Productivity, McKinsey Global Institute, San Francisco, CA.

Maroufkhani, P., Ismail, W. K. W., & Ghobakhloo, M. (2020). Big data analytics adoption model for small and medium enterprises. Journal of Science and Technology Policy Management, 11(4), 483-513.

Maroufkhani, P., Tseng, M.-L., Iranmanesh, M., Ismail, W.K.W. and Khalid, H. (2020), "Big data analytics adoption: determinants and performances among small to medium-sized enterprises", International Journal of Information Management, Elsevier, Vol. 54, p. 102190.

Marr, B. (2021), "The 4 biggest trends in Big Data and analytics right for 2021", available at: https://www.forbes.com/sites/bernardmarr/2021/02/22/the-4-biggest-trends-in-big-

Martınez-Olvera, C. and Mora-Vargas, J. (2019), "A comprehensive framework for the analysis of industry 4.0 value domains", Sustainability, Vol. 11 No. 10, p. 2960

Mazzei, M.J. and Noble, D. (2017), "Big data dreams: a framework for corporate strategy", Business Horizons, Vol. 60 No. 3, pp. 405-414.

Mcafee, A., Brynjolfsson, E., Davenport, T.H., Patil, D. and Barton, D. (2012), "Big data: the management revolution", Harvard Business Review, Vol. 90 No. 10, pp. 60-68.

Mehmood, R., & Graham, G. (2015). Big data logistics: A health-care transport capacity sharing model. Procedia Computer Science, 64, 1107-1114.

Mikalef, P., Pappas, I. O., Krogstie, J., & Giannakos, M. (2019). Big data analytics capabilities: a systematic literature review and research agenda. Information Systems and e-Business Management, 16(3), 547-578.

Mishra, N., and Rane, S.B. (2019), "Prediction and improvement of iron casting quality through analytics and Six Sigma approach", International Journal of Lean Six Sigma, Vol. 10 No. 1, pp. 189-210.

Moktadir, M.A., Ali, S.M., Paul, S.K. and Shukla, N. (2019), "Barriers to big data analytics in manufacturing supply chains: a case study from Bangladesh", Computers and Industrial Engineering, Vol. 128, pp. 1063-1075

Mortenson, M. J., Doherty, N. F., & Robinson, S. (2015). Operational research from Taylorism to Terabytes: A research agenda for the analytics age. European Journal of Operational Research, 241(3), 583-595.

Muduli, K., Govindan, K., Barve, A. and Geng, Y. (2013), "Barriers to green supply chain management in Indian mining industries: a graph theoretic approach", Journal of Cleaner Production, Vol. 47, pp. 335-344

Mukhopadhyay, S. C., Tyagi, S. K. S., Suryadevara, N. K., Piuri, V., Scotti, F., & Zeadally, S. (2021). Artificial intelligence-based sensors for next generation IoT applications: a review. IEEE Sensors Journal, 21(22), 24920-24932.

Mustapha, M. A., Manan, Z. A., & Alwi, S. R. W. (2017). Sustainable Green Management System (SGMS)–An integrated approach towards organizational sustainability. Journal of Cleaner Production, 146, 158-172.

Nozari, H., Fallah, M., Kazemipoor, H., & Najafi, S. E. (2021). Big data analysis of IoT-based supply chain management considering FMCG industries. Business Informatics 15(1), 78-96.

Nunnally, J.C. and Bernstein, I.H. (1994) The Assessment of Reliability. Psychometric Theory, 3, 248-292.

Nwankpa, J. and Roumani, Y. (2014), "Understanding the link between organizational learning capability and ERP system usage: an empirical examination", Computers in Human Behavior, Elsevier, Vol. 33, pp. 224-234.

OECD (2017), "Enhancing the contributions of SMEs in a global and digitalized economy", Meeting of the OECD Council at Ministerial Level.

Oliveira, T., and Martins, M. F. (2011). Literature review of information technology adoption models at firm level. The Electronic Journal Information Systems Evaluation, 14(1), 110–121.

Oncioiu, I., Bunget, O.C., Turkes, M.C., Capus¸neanu, S., Topor, D.I., Tamas¸, A.S., Rakos¸, I.-S. and Hint, M. S. (2019), "The impact of big data analytics on company performance in supply chain management", Sustainability, Multidisciplinary Digital Publishing Institute, Vol. 11 No. 18, p. 4864

Ozkan-Ozen, Y.D., Kazancoglu, Y. and Kumar Mangla, S. (2020), "Synchronized barriers for circular supply chains in industry 3.5/industry 4.0 transition for sustainable resource management", Resources, Conservation and Recycling, Vol. 161, p. 104986.

Papadopoulos, T., Gunasekaran, A., Dubey, R., Altay, N., Childe, S. J., & Fosso-Wamba, S. (2017). The role of Big Data in explaining disaster resilience in supply chains for sustainability. Journal of Cleaner Production, 142, 1108-1118.

Pham, T.T., Kuo, T.-C., Tseng, M.-L., Tan, R.R., Tan, K., Ika, D.S., and Lin, C.J. (2019), "Industry 4.0 to accelerate the circular economy: a case study of electric scooter sharing", Sustainability, Vol. 11 No. 23, p. 6661.

Pinto, C.A.S., Reis, A.D.C. and Braga, M. (2020), "The supply chain as part of knowledge management in organisational environments", International Journal of Logistics Systems and Management, Vol. 36 No. 3, p. 385.

Piyathanavong, V., Garza-Reyes, J. A., Kumar, V., Maldonado-Guzmán, G., & Mangla, S. K. (2019). The adoption of operational environmental sustainability approaches in the Thai manufacturing sector. Journal of Cleaner Production, 220, 507-528.

Popovic, A., Hackney, R., Tassabehji, R., & Castelli, M. (2018). The impact of big data analytics on firms' high value business performance. Information Systems Frontiers, 20(2), 209-222.

Premkumar, G. (2003), "A meta-analysis of research on information technology implementation in small business", Journal of Organizational Computing and Electronic Commerce, Vol. 13 No. 2, pp. 91-121.

Premkumar, G. and Ramamurthy, K. (1995), "The role of interorganizational and organizational factors on the decision mode for adoption of interorganizational systems", Decision Sciences, Vol. 26 No. 3, pp. 303-336.

Priyadarshinee, P., Raut, R. D., Jha, M. K., and Gardas, B. B. (2017). Understanding and predicting the determinants of cloud computing adoption: A two staged hybrid SEM-neural networks approach. Computers in Human Behavior, 76, 341-362.

Rachinger, M., Rauter, R., Muller, C., Vorraber, W. and Schirgi, E. (2019), € "Digitalization and its influence on business model innovation", Journal of Manufacturing Technology Management, Vol. 30 No. 8, pp. 1143-1160.

Raguseo, E. and Vitari, C. (2018), "Investments in big data analytics and firm performance: an empirical investigation of direct and mediating effects", International Journal of Production Research, Vol. 56 No. 15, pp. 1-16.

Rajput, S., and Singh, S.P. (2019), "Connecting circular economy and industry 4.0", International Journal of Information Management, Vol. 49, pp. 98-113.

Rakhman, R., Widiastuti, R., Legowo, N., & Kaburuan, E. M. (2019). Big data analytics implementation in banking industry–Case study cross selling activity in Indonesia's Commercial bank. International Journal of Scientific & Technology Research, 8(9), 1632-1643.

Ram, J., Afridi, N. K., & Khan, K. A. (2019). Adoption of Big Data analytics in construction: development of a conceptual model. Built Environment Project and Asset Management.

Raman, S., Patwa, N., Niranjan, I., Ranjan, U., Moorthy, K., & Mehta, A. (2018). Impact of big data on supply chain management. International Journal of Logistics Research and Applications, 21(6), 579-596.

Ramanathan, R., Philpott, E., Duan, Y., & Cao, G. (2017). Adoption of business analytics and impact on performance: A qualitative study in retail. Production Planning & Control, 28(11-12), 985-998.

Raut, R.D., Mangla, S.K., Narwane, V.S., Gardas, B.B., Priyadarshinee, P. and Narkhede, B.E. (2019), "Linking big data analytics and operational sustainability practices for sustainable business management", Journal of Cleaner Production, Elsevier, Vol. 224, pp. 10-24

Ren, S., Zhang, Y., Liu, Y., Sakao, T., Huisingh, D., and Almeida, C.M.V.B. (2019), "A comprehensive review of big data analytics throughout product lifecycle to support sustainable smart manufacturing: a framework, challenges and future research directions", Journal of Cleaner Production, Vol. 210, pp. 1343-1365.

Ren, S.J.-F., Wamba, S.F., Akter, S., Dubey, R., and Childe, S.J. (2017), "Modelling quality dynamics, business value and firm performance in a big data analytics environment", International Journal of Production Research, Vol. 55 No. 17, pp. 5011-5026.

Rogers, Everett M. (1962). Diffusion of innovations. New York: Free Press of Glencoe

Rogers, Everett M. (1995). Diffusion of Innovations. New York: Free Press.

Rogers, Everett M. (2003). Diffusion of innovation (5th ed.). New York: Free Press.

Roy, A., & Goll, I. (2014). Predictors of various facets of sustainability of nations: The role of cultural and economic factors. International Business Review, 23(5), 849-861.

Roy, M. and Roy, A. (2019), "Nexus of internet of things (IoT) and big data: roadmap for smart management systems (SMgS)", IEEE Engineering Management Review, IEEE, Vol. 47 No. 2, pp. 53-65.

Roy, V. and Singh, S. (2017), "Mapping the business focus in sustainable production and consumption literature: review and research framework", Journal of Cleaner Production, Vol. 150, pp. 224-236

Ruiz-Benitez, R., López, C., & Real, J. C. (2018). Achieving sustainability through the lean and resilient management of the supply chain. International Journal of Physical Distribution & Logistics Management. 49 (2), 122–155.

Russom, P. (2011). Big data analytics. TDWI Best Practices Report, Fourth Quarter, 19(4), 1-34.

Saaty TL (1980) The analytic hierarchy process. McGraw-Hill, New York, p 324

Saaty TL (2000) Fundamentals of decision making and priority theory with the analytic hierarchy process. Vol. 6 RWS publications

Saaty, T.L. (1994) 'How to make a decision: the analytic hierarchy process', Interfaces, Vol. 24, No. 6, pp.19–43

Sahay, B. S., & Ranjan, J. (2008). Real time business intelligence in supply chain analytics. Information Management & Computer Security, 16(1), 28-48.

Saleem, H., Li, Y., Ali, Z., Ayyoub, M., Wang, Y. and Mehreen, A. (2020), "Big data use and its outcomes in supply chain context: the roles of information sharing and technological innovation", Journal of Enterprise Information Management, Vol. 34 No. 4

Salehan, M. and Kim, D.J. (2016), "Predicting the performance of online consumer reviews: a sentiment mining approach to big data analytics", Decision Support Systems, Vol. 81, pp. 30-40.

Samaie, F., Javadi, S., Meyar-Naimi, H., & Feshki-Farahani, H. (2020). Environmental sustainability policy on plug-in hybrid electric vehicle penetration utilizing fuzzy TOPSIS and game theory. Clean Technologies and Environmental Policy, 22(4), 787-801.

Sanders NR (2016) How to use big data to drive your supply chain. Calif Manage Rev 58:26–48. https ://doi.org/10.1525/ cmr.2016.58.3.26

Scavarda, A., Dau, G., Felipe Scavarda, L., Duarte Azevedo, B. and Luis Korzenowski, A. (2020), "Social and ecological approaches in urban interfaces: a sharing economy management framework", Science of The Total Environment, Vol. 713, p. 134407

Schilling, M.A. & Steensma, H.K. 2001 the use of modular organizational forms: An industry-level analysis. Academy of Management Journal, 44:1149-1168.

Schoenherr, T., & Speier-Pero, C. (2015). Data science, predictive analytics, and big data in supply chain management: Current state and future potential. Journal of Business Logistics, 36(1), 120-132.

Schull, A. and Maslan, N. (2018), "On the adoption of big data analytics: interdependencies of contextual factors", Proceedings of the 20th International Conference on Enterprise Information Systems, Funchal, Madeira, Portugal, Scitepress - Science and Technology Publications, pp. 425-431.

Sekaran, U. (2003) Research Methods for Business: A Skill-Building Approach. 4th Edition, John Wiley & Sons, New York

Sen, D., Ozturk, M. and Vayvay, O. (2016), "An overview of big data for growth in SMEs", Procedia -Social and Behavioral Sciences, Vol. 235, pp. 159-167.

Seth, D., Rehman, M.A.A. and Shrivastava, R.L. (2018), "Green manufacturing drivers and their relationships for small and medium (SME) and large industries", Journal of Cleaner Production, Vol. 198, pp. 1381-1405.

Sethi, A. K., and S. P. Sethi. (1990). "Flexibility in Manufacturing: A Survey." International Journal of Flexible Manufacturing Systems 2 (4): 289–328.

Sharma, M., & Garg, N. (2016). Inventory control and big data. In M. Mittal, & N. H. Shah (Eds.), Optimal Inventory Control and Management Techniques 222-235, Hershey: IGI Global.

Sharma, R., Jabbour, C.J.C. and Lopes de Sousa Jabbour, A.B. (2020), "Sustainable manufacturing and industry 4.0: what we know and what we don’t", Journal of Enterprise Information Management

Sharma, V.K., Chandna, P. and Bhardwaj, A. (2017), "Green supply chain management related performance indicators in agro industry: a review", Journal of Cleaner Production, Vol. 141, pp. 1194-1208.

Shibin, K.T., Gunasekaran, A. and Dubey, R. (2017a), "Explaining sustainable supply chain performance using a total interpretive structural modeling approach", Sustainable Production and Consumption, Vol. 12, pp. 104-118.

Shibin, K.T., Gunasekaran, A. and Dubey, R. (2017b), "Flexible sustainable manufacturing via decision support simulation: a case study approach", Sustainable Production and Consumption, Vol. 12, pp. 206-220.

Shin and Kim, (2016). Forecasting short-term air passenger demand using big data from search engine queries. Automation in Construction, 70, 98-108.

Shin, D.-H. (2016), "Demystifying big data: anatomy of big data developmental process", Telecommunications Policy, Vol. 40 No. 9, pp. 837-854.

Singh RK (2012) Justifcation of coordinated supply chain in small and medium enterprises using analytic hierarchy process. International Journal of Services Sciences 277-293.

Singh RK (2013) Prioritizing the factors for coordinated supply chain using analytic hierarchy process (AHP). Measuring Business Excellence17:80– 97.

Singh RK, and Agrawal S (2018) Analyzing disposition strategies in reverse supply chains: fuzzy TOPSIS approach. Management of Environmental Quality: An International Journal 29:427–443.

Singh SK, and El-Kassar A-N (2019) Role of big data analytics in developing sustainable capabilities. Journal of cleaner production 213:1264–1273.

Singh, R. K., Luthra, S., Mangla, S. K., & Uniyal, S. (2019a). Applications of information and communication technology for sustainable growth of SMEs in India food industry. Resources, Conservation and Recycling, 147, 10-18.

Singh, R.K. and Kumar, P. (2019), "Measuring the flexibility index for a supply chain using graph theory matrix approach", Journal of Global Operations and Strategic Sourcing, Vol. 13 No. 1, pp. 56-69.

Singh, R.K. and Kumar, R. (2020), "Strategic issues in supply chain management of Indian SMEs due to globalization: an empirical study", Benchmarking: An International Journal, Emerald Publishing, Vol. 27 No. 3, pp. 913-932.

Singh, R.K., Kumar, P. and Chand, M. (2019a), "Evaluation of supply chain coordination index in context to Industry 4.0 environment", Benchmarking: An International Journal, Vol. 28 No. 5, BIJ-07-2018-0204.

Sivarajah, U., Kamal, M.M., Irani, Z. and Weerakkody, V. (2017), "Critical analysis of Big Data challenges and analytical methods", Journal of Business Research, Elsevier, Vol. 70, pp. 263-286

Song M, Fisher R, Kwoh Y (2019) Technological challenges of green innovation and sustainable resource management with large scale data. Technol Forecast Soc Change 144:361–368.

Srinivasan, R., and Swink, M. (2015). Leveraging supply chain integration through planning comprehensiveness: An organizational information processing theory perspective. Decision Sciences, 46(5), 823-861.

Stefanovic, N. (2014). Proactive supply chain performance management with predictive analytics. The Scientific World Journal, 2014, 1-17.

Stock, T. and Seliger, G. (2016), "Opportunities of sustainable manufacturing in industry 4.0", Procedia CIRP, Vol. 40, pp. 536-541.

Sun, S., Cegielski, C.G., Jia, L., and Hall, D.J. (2018), "Understanding the factors affecting the organizational adoption of big data", Journal of Computer Information Systems, Taylor & Francis, Vol. 58 No. 3, pp. 193-203.

Sun, S., Hall, D. J., & Cegielski, C. G. (2020). Organizational intention to adopt big data in the B2B context: An integrated view. Industrial Marketing Management, 86, 109-121.

Takata, M., Lin, B.L., Xue, M., Zushi, Y., Terada, A. and Hosomi, M. (2020), "Predicting the acute ecotoxicity of chemical substances by machine learning using graph theory", Chemosphere, Vol. 238, 124604

Tan, K.H., Zhan, Y., Ji, G., Ye, F. and Chang, C. (2015), "Harvesting big data to enhance supply chain innovation capabilities: an analytic infrastructure based on deduction graph", International Journal of Production Economics, Vol. 165, pp. 223-233.

Tan, K.H.; Zhan, Y. (2017) Improving new product development using big data: A case study of an electronics company. R D Management 47, 570–582

Telukdarie, A., Buhulaiga, E., Bag, S., Gupta, S., & Luo, Z. (2018). Industry 4.0 implementation for multinationals. Process Safety and Environmental Protection, 118, 316-329.

Thakur, V., and Mangla, S.K. (2019), "Change management for sustainability: evaluating the role of human, operational and technological factors in leading Indian firms in home appliances sector", Journal of Cleaner Production, Vol. 213, pp. 847-862

Tippins, M. J., and Sohi, R. S. (2003). IT competency and firm performance: is organizational learning a missing link? Strategic management journal, 24(8), 745-761.

Tiwari, S., Wee, H. M., & Daryanto, Y. (2018). Big data analytics in supply chain management between 2010 and 2016: Insights to industries. Computers & Industrial Engineering, 115, 319-330.

To, M. L., and Ngai, E. W. (2006). Predicting the organizational adoption of B2C e-commerce: An empirical study. Industrial Management and Data Systems, 106(8), 1133–1147.

Tormay, P. (2015). Big data in pharmaceutical R&D: creating a sustainable R&D engine. Pharmaceutical Medicine, 29(2), 87-92.

Tornatzky, L.G., Fleischer, M. and Chakrabarti, A.K. (1990), The Processes of Technological Innovation, Lexington Books.

Trochim, W. M. K. (2006). The Qualitative Debate. Research Methods Knowledge Base. http://www.socialresearchmethods.net/kb/qualmeth.php

Tseng, M. L., Lim, M. K., & Wu, K. J. (2019). Improving the benefits and costs on sustainable supply chain finance under uncertainty. International Journal of Production Economics, 218, 308-321.

Upton, D. M. 1994. "The Management of Manufacturing Flexibility." California Management Review 36 (2): 72–89.

Vargas, J.R.C., Mantilla, C.E.M. and de Sousa Jabbour, A.B.L. (2018), "Enablers of sustainable supply chain management and its effect on competitive advantage in the Colombian context", Resources, Conservation and Recycling, Elsevier, Vol. 139, pp. 237-250.

Vera-Baquero, A., Colomo Palacios, R., Stantchev, V., & Molloy, O. (2015). Leveraging big-data for business process analytics. The Learning Organization, 22(4), 215-228.

Verma, S. (2017), "The adoption of big data services by manufacturing firms: an empirical investigation in India", Journal of Information Systems and Technology Management, Vol. 14 No. 1, pp. 39-68.

Verma, S., & Bhattacharyya, S. S. (2017). Perceived strategic value-based adoption of Big Data Analytics in emerging economy: A qualitative approach for Indian firms. Journal of Enterprise Information Management, 30(3), 354-382.

Verma, S., & Chaurasia, S. (2019). Understanding the determinants of big data analytics adoption. Information Resources Management Journal (IRMJ), 32(3), 1-26.

Virmani, N., Bera, S., & Kumar, R. (2020). Identification and testing of barriers to sustainable manufacturing in the automobile industry: a focus on Indian MSMEs. Benchmarking: An International Journal.

Waller, M. A., & Fawcett, S. E. (2013). Data science, predictive analytics, and big data: a revolution that will transform supply chain design and management. Journal of Business Logistics, 34(2), 77-84.

Wamba, S. F., Gunasekaran, A., Akter, S., Ren, S. J. F., Dubey, R., & Childe, S. J. (2017). Big data analytics and firm performance: Effects of dynamic capabilities. Journal of Business Research, 70, 356-365.

Wang, G., Gunasekaran, A., Ngai, E. W., & Papadopoulos, T. (2016a). Big data analytics in logistics and supply chain management: Certain investigations for research and applications. International Journal of Production Economics, 176, 98-110.

Wang, H., Xu, Z., Fujita, H. & Liu, S., (2016b). Towards felicitous decision making: An overview on challenges and trends of Big Data. Information Sciences, 367, 747-765.

Wang, Y. M., Wang, Y. S., & Yang, Y. F. (2010). Understanding the determinants of RFID adoption in the manufacturing industry. Technological Forecasting and Social Change, 77(5), 803-815.

Wang, Y., and Wang, Y. (2016). Determinants of firms' knowledge management system implementation: an empirical study. Computers In Human Behaviour, 64(1), 829–842.

Wang, Y., and Wiebe, V.J. (2016), "Big Data analytics on the characteristic equilibrium of collective opinions in social networks", Big Data: Concepts, Methodologies, Tools, and Applications, IGI Global, Hershey, Pennsylvania, pp. 1403-1420

Wang, Z., Xue, M., Wang, Y., Song, M., Li, S., Daziano, R. A., & Zhang, B. (2019). Big data: New tend to sustainable consumption research. Journal of Cleaner Production, 236, 117499.

Watson, H.J. (2019), "Update tutorial: big data analytics: concepts, technology, and applications", Communications of the Association for Information Systems, Vol. 44 No. 1, p. 21

Weerakkody V, Kapoor K, Balta ME et al (2017) Factors influencing user acceptance of public sector big open data. Prod Plan Control 28:891–905.

Weigelt, C. and Sarkar, M. (2009), "Learning from supply-side agents: the impact of technology solution providers' experiential diversity on clients' innovation adoption", Academy of Management Journal, Vol. 52 No. 1, pp. 37-60.

Weng, W. H., & Weng, W. T. (2013). Forecast of development trends in big data industry. In Y. K. Lin., Y. C. Tsao., and S.W. Lin (Eds.), Proceedings of the Institute of Industrial Engineers Asian Conference 2013. (pp. 1487-1494). Springer, Singapore.

White, M. (2012). Digital workplaces: Vision and reality. Business Information Review, 29(4), 205-214.

Wilcox T, Jin N, Flach P, Thumim J (2019) A big data platform for smart meter data analytics. Computers in Industry 105:250–259.

Williams, N., Ferdinand, N.P. and Croft, R. (2014), "Project management maturity in the age of big data", International Journal of Managing Projects in Business, Vol. 7 No. 2, pp. 311-317.

Wood, L. C., Wang, C., Abdul-Rahman, H., & Abdul-Nasir, N. S. J. (2016). Green hospital design: integrating quality function deployment and end-user demands. Journal of Cleaner Production, 112, 903-913.

Wu, K.-J., Liao, C.-J., Tseng, M.-L., Lim, M.K., Hu, J. and Tan, K. (2017), "Toward sustainability: using big data to explore the decisive attributes of supply chain risks and uncertainties", Journal of Cleaner Production, Vol. 142, pp. 663-676.

Yaqoob I, Hashem IAT, Gani A et al (2016) Big data: from beginning to future. International Journal of Information Management 36:1231–1247.

Yasmin, M., Tatoglu, E., Kilic, H. S., Zaim, S., & Delen, D. (2020). Big data analytics capabilities and firm performance: An integrated MCDM approach. Journal of Business Research, 114, 1-15.

Ye, L., Pan, S.L., Wang, J., Wu, J. and Dong, X. (2021), "Big data analytics for sustainable cities: an information triangulation study of hazardous materials transportation", Journal of Business Research, Vol. 128, pp. 381-390.

Zhang, Y., Ren, S., Liu, Y. and Si, S. (2017), "A big data analytics architecture for cleaner manufacturing and maintenance processes of complex products", Journal of Cleaner Production, Vol. 142, pp. 626-641

Zhong RY, Huang GQ, Lan S et al (2015) A big data approach for logistics trajectory discovery from RFID-enabled production data. Int J Prod Econ 165:260–272.

Zhong, R. Y., Newman, S. T., Huang, G. Q., & Lan, S. (2016). Big Data for supply chain management in the service and manufacturing sectors: Challenges, opportunities, and future perspectives. Computers & Industrial Engineering, 101, 572-591.

Zhou, Y., Xu, L. and Muhammad Shaikh, G. (2019), "Evaluating and prioritizing the green supply chain management practices in Pakistan: based on Delphi and fuzzy AHP approach", Symmetry, Vol. 11 No. 11, p. 1346

Zhu, K., and Kraemer, K. L. (2005). Post-adoption variations in usage and value of e-business by organizations: Cross-country evidence from the retail industry. Information Systems Research, 16(1), 61–84.

Zhu, K., Dong, S., Xu, S.X. and Kraemer, K.L. (2006), "Innovation diffusion in global contexts: determinants of post-adoption digital transformation of European companies", European Journal of Information Systems, Vol. 15 No. 6, pp. 601-616.

Zhu, S., Song, J., Hazen, B. T., Lee, K., & Cegielski, C. (2018). How supply chain analytics enables operational supply chain transparency: An organizational information processing theory perspective. International Journal of Physical Distribution & Logistics Management, 48(1), 47-68.

Zimmermann, H. J. (1985). Applications of fuzzy set theory to mathematical programming. Information sciences, 36(1-2), 29-58.

APPENDIX-A1

Thomas Saaty's scale for pair wise comparison of criteria (Saaty, 1994)

Importance intensity	**Terminology**	**Explanation**
1	Equal importance	Allocate dissimilar value to each element depending on the significance of factor on another factor. If two factors have equal significance, then intensity of significance should be unity and one is allocated to both factors. Therefore, allocate value 3, 5, 7, 9 or the value of two adjoining judgments, i.e., 2, 4, 6, 8 is depending on the significance of each factor.
3	Weak importance of one over another	
5	Essential or strong importance	
7	Highly strong importance	
9	Extreme/supreme importance	
2, 4, 6, 8	Intermediate, middle values of two adjoining judgments	
Reciprocals	Allocate any one number from previously mentioned value to activity i when it is compared with j, and allocated the corresponding of its value when the activity j compared to i.	

Appendix A2

Average random index value (Saaty, 2000)

Size of matrix (n)	1	2	3	4	5	6	7	8	9	10
Random Consistency Index (RCI)	0	0	0.52	0.9	1.1	1.25	1.35	1.4	1.45	1.49

Appendix A3

Let P_1 be the pair wise comparison matrix and P_2 principal vector matrix

$$P_1 = \begin{bmatrix} 1 & 0.143 & 0.25 & 0.2 & 0.2 & 0.33 & 0.125 \\ 7 & 1 & 5 & 3 & 2 & 6 & 0.33 \\ 4 & 0.2 & 1 & 0.33 & 0.2 & 5 & 0.25 \\ 5 & 0.33 & 3 & 1 & 0.33 & 4 & 0.2 \\ 5 & 0.5 & 5 & 3 & 1 & 7 & 0.5 \\ 3 & 0.167 & 0.2 & 0.25 & 0.143 & 1 & 0.167 \\ 8 & 3 & 4 & 5 & 2 & 6 & 1 \end{bmatrix}$$

$$P_2 = \begin{bmatrix} 0.025 \\ 0.2260 \\ 0.0765 \\ 0.1030 \\ 0.1940 \\ 0.0395 \\ 0.3360 \end{bmatrix} \quad P_3 = P_1 * P_2 = \begin{bmatrix} 0.19087 \\ 1.8283 \\ 0.5750 \\ 0.8213 \\ 1.568 \\ 0.2421 \\ 2.660 \end{bmatrix} \text{ and } P_4 = P_3 / P_2 = \begin{bmatrix} 7.634 \\ 8.089 \\ 7.528 \\ 7.973 \\ 8.082 \\ 7.015 \\ 7.916 \end{bmatrix}$$

λ max, Average of the element of P_4 = 7.7481

Now, consistency Index (CI) = $\frac{\lambda \max - n}{n-1}$ = (7.7481-7) / (7-1) = 0.12468

And consistency ratio (CR) = CI/RCI = (n Appendix A2)

CR = 0.12468/1.35 0.0923, i.e., CR<0.1. So, result is consistent

Appendix A4

Fuzzy Decision matrix D

	1	2	3	4	5	6	7
C-1	(0.7,0.9,1.0)	(0.1,0.3,0.5)	(0.7,0.9,1.0)	(0.3,0.5,0.7)	(0.1,0.3,0.5)	(0.1,0.3,0.5)	(0.1,0.3,0.5)
C-2	(0.7,0.9,1.0)	(0.7,0.9,1.0)	(0.7,0.9,1.0)	(0.5,0.7,0.9)	(0.3,0.5,0.7)	(0.5,0.7,0.9)	(0.5,0.7,0.9)
C-3	(0.7,0.9,1.0)	(0.7,0.9,1.0)	(0.3,0.5,0.7)	(0.5,0.7,0.9)	(0.3,0.5,0.7)	(0.5,0.7,0.9)	(0.5,0.7,0.9)
C-4	(0.3,0.5,0.7)	(0.3,0.5,0.7)	(0.1,0.3,0.5)	(0.5,0.7,0.9)	(0.1,0.3,0.5)	(0.3,0.5,0.7)	(0.3,0.5,0.7)
C-5	(0.3,0.5,0.7)	(0.5,0.7,0.9)	(0.7,0.9,1.0)	(0.1,0.3,0.5)	(0.3,0.5,0.7)	(0.3,0.5,0.7)	(0.1,0.3,0.5)
C-6	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.7,0.9,1.0)	(0.5,0.7,0.9)	(0.7,0.9,1.0)	(0.5,0.7,0.9)	(0.1,0.3,0.5)
C-7	(0.7,0.9,1.0)	(0.5,0.7,0.9)	(0.7,0.9,1.0)	(0.5,0.7,0.9)	(0.3,0.5,0.7)	(0.5,0.7,0.9)	(0.3,0.5,0.7)
C-8	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.3,0.5,0.7)	(0.1,0.3,0.5)	(0.7,0.9,1.0)	(0.3,0.5,0.7)
C-9	(0.7,0.9,1.0)	(0.7,0.9,1.0)	(0.5,0.7,0.9)	(0.3,0.5,0.7)	(0.7,0.9,1.0)	(0.5,0.7,0.9)	(0.5,0.7,0.9)
C-10	(0.5,0.7,0.9)	(0.7,0.9,1.0)	(0.3,0.5,0.7)	(0.3,0.5,0.7)	(0.1,0.3,0.5)	(0.5,0.7,0.9)	(0.5,0.7,0.9)
C-11	(0.5,0.7,0.9)	(0.7,0.9,1.0)	(0.1,0.3,0.5)	(0.5,0.7,0.9)	(0.3,0.5,0.7)	(0.5,0.7,0.9)	(0.3,0.5,0.7)
C-12	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.3,0.5,0.7)	(0.3,0.5,0.7)	(0.3,0.5,0.7)	(0.3,0.5,0.7)
C-13	(0.5,0.7,0.9)	(0.3,0.5,0.7)	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.3,0.5,0.7)	(0.3,0.5,0.7)
C-14	(0.5,0.7,0.9)	(0.3,0.5,0.7)	(0.3,0.5,0.7)	(0.3,0.5,0.7)	(0.3,0.5,0.7)	(0.3,0.5,0.7)	(0.3,0.5,0.7)
C-15	(0.1,0.3,0.5)	(0.3,0.5,0.7)	(0.1,0.3,0.5)	(0.3,0.5,0.7)	(0.1,0.3,0.5)	(0.1,0.3,0.5)	(0.3,0.5,0.7)

Appendix A5

Un-weighted fuzzy matrix R

	1			2			3			4			5			6			7		
C-1	0.7	0.9	1	0.1	0.3	0.5	0.7	0.9	1	0.3	0.5	0.7	0.1	0.3	0.5	0.1	0.3	0.5	0.1	0.3	0.5
C-2	0.7	0.9	1	0.7	0.9	1	0.7	0.9	1	0.5	0.7	0.9	0.3	0.5	0.7	0.5	0.7	0.9	0.5	0.7	0.9
C-3	0.7	0.9	1	0.7	0.9	1	0.3	0.5	0.7	0.5	0.7	0.9	0.3	0.5	0.7	0.5	0.7	0.9	0.5	0.7	0.9
C-4	0.3	0.5	0.7	0.3	0.5	0.7	0.1	0.3	0.5	0.5	0.7	0.9	0.1	0.3	0.5	0.3	0.5	0.7	0.3	0.5	0.7
C-5	0.3	0.5	0.7	0.5	0.7	0.9	0.7	0.9	1	0.1	0.3	0.5	0.3	0.5	0.7	0.3	0.5	0.7	0.1	0.3	0.5
C-6	0.5	0.7	0.9	0.5	0.7	0.9	0.7	0.9	1	0.5	0.7	0.9	0.7	0.9	1	0.5	0.7	0.9	0.7	0.9	1
C-7	0.7	0.9	1	0.5	0.7	0.9	0.7	0.9	1	0.5	0.7	0.9	0.3	0.5	0.7	0.5	0.7	0.9	0.3	0.5	0.7
C-8	0.5	0.7	0.9	0.5	0.7	0.9	0.5	0.7	0.9	0.3	0.5	0.7	0.1	0.3	0.5	0.7	0.9	1	0.3	0.5	0.7
C-9	0.7	0.9	1	0.7	0.9	1	0.5	0.7	0.9	0.3	0.5	0.7	0.7	0.9	1	0.5	0.7	0.9	0.5	0.7	0.9
C-10	0.5	0.7	0.9	0.7	0.9	1	0.3	0.5	0.7	0.3	0.5	0.7	0.1	0.3	0.5	0.5	0.7	0.9	0.5	0.7	0.9
C-11	0.5	0.7	0.9	0.7	0.9	1	0.1	0.3	0.5	0.5	0.7	0.9	0.3	0.5	0.7	0.5	0.7	0.9	0.3	0.5	0.7
C-12	0.3	0.5	0.7	0.5	0.7	0.9	0.5	0.7	0.9	0.3	0.5	0.7	0.3	0.5	0.7	0.3	0.5	0.7	0.3	0.5	0.7
C-13	0.5	0.7	0.9	0.3	0.5	0.7	0.5	0.7	0.9	0.5	0.7	0.9	0.5	0.7	0.9	0.3	0.5	0.7	0.3	0.5	0.7
C-14	0.5	0.7	0.9	0.3	0.5	0.7	0.3	0.5	0.7	0.3	0.5	0.7	0.3	0.5	0.7	0.3	0.5	0.7	0.3	0.5	0.7
C-15	0.1	0.3	0.5	0.3	0.5	0.7	0.1	0.3	0.5	0.3	0.5	0.7	0.1	0.3	0.5	0.1	0.3	0.5	0.3	0.5	0.7

Appendix A6

Distance of the ratings of each factor from A^+ with respect to each criterion

	1	2	3	4	5	6	7	D+
C-1	0.981	0.979	0.966	0.94	0.931	0.931	0.942	6.67
C-2	0.981	0.941	0.888	0.826	0.86	0.9	0.942	6.338
C-3	0.981	0.941	0.888	0.826	0.87	0.919	0.967	6.391
C-4	0.989	0.971	0.942	0.9	0.919	0.946	0.98	6.647
C-5	0.989	0.958	0.916	0.86	0.879	0.906	0.942	6.45
C-6	0.984	0.955	0.914	0.86	0.879	0.906	0.942	6.441
C-7	0.981	0.953	0.914	0.86	0.879	0.906	0.942	6.434
C-8	0.984	0.955	0.914	0.86	0.884	0.915	0.953	6.467
C-9	0.981	0.941	0.888	0.826	0.865	0.909	0.953	6.363
C-10	0.984	0.943	0.889	0.826	0.87	0.919	0.967	6.398
C-11	0.984	0.943	0.889	0.826	0.875	0.928	0.98	6.426
C-12	0.989	0.958	0.916	0.86	0.884	0.915	0.953	6.476
C-13	0.984	0.968	0.94	0.9	0.91	0.928	0.953	6.583
C-14	0.984	0.968	0.94	0.9	0.914	0.937	0.967	6.611
C-15	0.993	0.974	0.943	0.9	0.919	0.946	0.98	6.656

Appendix A7

Distance of the ratings of each factor from A^- with respect to each criterion

	1	2	3	4	5	6	7	D-
C-1	0.02	0.021	0.039	0.069	0.073	0.073	0.059	0.352
C-2	0.02	0.083	0.133	0.176	0.158	0.124	0.059	0.752
C-3	0.02	0.083	0.133	0.176	0.156	0.118	0.035	0.721
C-4	0.012	0.037	0.068	0.106	0.1	0.082	0.023	0.427
C-5	0.012	0.059	0.1	0.144	0.135	0.113	0.059	0.622
C-6	0.016	0.06	0.1	0.144	0.135	0.113	0.059	0.628
C-7	0.02	0.061	0.101	0.144	0.135	0.113	0.059	0.632
C-8	0.016	0.06	0.1	0.144	0.134	0.11	0.048	0.612
C-9	0.02	0.083	0.133	0.176	0.157	0.121	0.048	0.737
C-10	0.016	0.083	0.133	0.176	0.156	0.118	0.035	0.717
C-11	0.016	0.083	0.133	0.176	0.156	0.117	0.023	0.703
C-12	0.012	0.059	0.1	0.144	0.134	0.11	0.048	0.607
C-13	0.016	0.038	0.069	0.106	0.102	0.088	0.048	0.466
C-14	0.016	0.038	0.069	0.106	0.1	0.084	0.035	0.448
C-15	0.008	0.036	0.068	0.106	0.1	0.082	0.023	0.422

Appendix A8

Influence matrix X_1

	C-1	C-2	C-3	C-4	C-5	C-6	C-7	C-8	C-9	C-10	C-11	C-12	C-13	C-14	C-15
C-1	0	2	3	3	2	4	2	3	2	2	3	4	3	4	2
C-2	2	0	3	3	2	4	3	2	3	4	2	3	2	1	1
C-3	2	3	0	2	3	2	1	4	2	1	3	1	2	1	3

C-4	2	3	3	0	3	3	2	3	2	3	3	0	3	0	3
C-5	1	2	2	1	0	3	1	2	2	2	2	4	2	4	2
C-6	2	2	2	3	2	0	3	2	2	3	3	3	3	2	2
C-7	2	1	2	3	2	1	0	2	1	1	2	3	2	1	2
C-8	2	2	2	3	2	2	1	0	2	2	2	1	3	2	3
C-9	1	2	3	2	3	1	2	4	0	3	1	2	3	3	2
C-10	2	2	2	3	2	2	2	2	2	0	3	3	0	2	3
C-11	2	1	2	2	2	3	1	2	2	2	0	2	2	2	2
C-12	2	0	1	2	3	2	2	3	2	3	2	0	2	1	2
C-13	2	3	1	2	3	2	2	2	2	0	1	2	0	2	2
C-14	1	2	2	2	2	1	1	2	2	2	2	1	2	0	2
C-15	2	3	1	1	3	2	2	3	2	2	2	1	3	2	0

Influence matrix X_2

	C-1	C-2	C-3	C-4	C-5	C-6	C-7	C-8	C-9	C-10	C-11	C-12	C-13	C-14	C-15
C-1	0	2	3	3	2	4	2	3	2	2	3	4	3	4	2
C-2	2	0	3	3	2	4	3	2	3	4	2	3	2	1	1
C-3	2	3	0	2	3	2	1	4	2	1	3	1	2	1	3
C-4	2	3	3	0	3	3	2	3	2	3	3	0	3	0	3
C-5	1	2	2	1	0	3	1	2	2	2	2	4	2	4	2
C-6	2	2	2	3	2	0	3	2	2	3	3	3	3	2	2
C-7	2	1	2	3	2	1	0	2	1	1	2	3	2	1	2
C-8	2	2	2	3	2	2	1	0	2	2	2	1	3	2	3
C-9	1	2	3	2	3	1	2	4	0	3	1	2	3	3	2
C-10	2	2	2	3	2	2	2	2	2	0	3	3	0	2	3
C-11	2	1	2	2	2	3	1	2	2	2	0	2	2	2	2
C-12	2	0	1	2	3	2	2	3	2	3	2	0	2	1	2
C-13	2	3	1	2	3	2	2	2	2	0	1	2	0	2	2
C-14	1	2	2	2	2	1	1	2	2	2	2	1	2	0	2
C-15	2	3	1	1	3	2	2	3	2	2	2	1	3	2	0

Influence matrix X_3

	C-1	C-2	C-3	C-4	C-5	C-6	C-7	C-8	C-9	C-10	C-11	C-12	C-13	C-14	C-15
C-1	0	2	1	2	1	2	2	2	1	2	2	2	2	1	2
C-2	3	0	2	0	1	3	3	3	2	2	2	2	3	2	1
C-3	3	3	0	1	2	2	2	2	1	1	2	2	2	2	1
C-4	2	4	2	0	2	1	2	2	2	3	1	1	2	2	3
C-5	2	3	2	2	0	2	2	2	2	3	2	2	2	2	3
C-6	4	3	2	2	3	0	3	2	1	2	3	2	2	1	2
C-7	2	2	1	2	1	1	0	1	2	2	1	2	2	1	2
C-8	3	3	3	3	2	2	2	0	3	2	2	2	2	2	3
C-9	2	2	2	2	2	1	2	2	0	2	2	2	2	2	2
C-10	3	3	2	2	2	2	3	3	3	0	2	2	0	2	3

C-11	3	3	2	2	2	2	3	2	1	1	0	2	3	2	2
C-12	4	0	1	1	4	3	3	1	1	2	4	0	3	1	1
C-13	2	3	1	2	2	1	3	2	3	0	2	3	0	2	2
C-14	4	0	1	1	4	1	2	2	2	2	2	1	2	0	2
C-15	2	3	2	2	2	2	2	3	1	2	2	1	3	2	0

Influence matrix X_4

	C-1	C-2	C-3	C-4	C-5	C-6	C-7	C-8	C-9	C-10	C-11	C-12	C-13	C-14	C-15
C-1	0	2	1	2	1	2	2	2	1	2	2	2	2	1	2
C-2	2	0	2	3	2	3	2	4	2	3	1	3	2	2	3
C-3	3	3	0	1	2	2	2	2	1	1	2	2	2	2	1
C-4	2	1	2	0	1	2	3	3	2	2	2	2	1	2	1
C-5	2	3	2	2	0	2	2	2	2	3	2	2	2	2	3
C-6	4	3	2	2	3	0	3	2	1	2	3	2	2	1	2
C-7	2	2	1	2	1	1	0	1	2	2	1	2	2	1	2
C-8	3	3	3	3	2	2	2	0	3	2	2	2	2	2	3
C-9	2	2	2	2	2	1	2	2	0	2	2	2	2	2	2
C-10	3	4	2	2	3	2	3	3	3	0	2	2	1	2	4
C-11	3	3	2	2	2	2	3	2	1	1	0	2	3	2	2
C-12	4	0	1	1	4	3	3	1	1	2	4	0	3	1	1
C-13	2	3	1	2	2	1	3	2	3	0	2	3	0	2	2
C-14	4	0	1	1	4	1	2	2	2	2	2	1	2	0	2
C-15	2	3	2	2	2	2	2	3	1	2	2	1	3	2	0

Influence matrix X_5

	C-1	C-2	C-3	C-4	C-5	C-6	C-7	C-8	C-9	C-10	C-11	C-12	C-13	C-14	C-15
C-1	0	1	1	2	1	2	2	2	1	2	2	2	2	1	2
C-2	3	0	3	1	3	2	2	3	4	3	2	3	4	1	3
C-3	2	3	0	1	2	1	2	3	1	2	2	2	1	1	2
C-4	2	0	2	0	2	3	1	1	2	2	1	2	3	2	1
C-5	2	2	2	2	0	3	2	3	2	2	2	2	3	2	2
C-6	1	2	1	2	1	0	2	2	2	2	1	1	2	1	1
C-7	2	4	1	2	3	2	0	3	1	2	3	3	2	2	1
C-8	2	1	2	1	2	3	2	0	1	2	2	2	2	1	2
C-9	2	2	2	2	3	2	2	2	0	2	2	2	3	2	1
C-10	3	3	2	2	2	3	2	3	3	0	2	3	1	2	2
C-11	2	3	2	2	2	2	2	3	1	3	0	3	1	2	2
C-12	1	2	1	2	2	1	2	2	1	3	3	0	2	1	2
C-13	2	2	2	2	2	2	3	3	3	1	2	3	0	1	1
C-14	2	4	1	1	4	2	1	1	2	2	2	2	2	0	1
C-15	3	2	2	2	2	1	1	3	1	3	2	2	2	2	0

Influence matrix X_6

	C-1	C-2	C-3	C-4	C-5	C-6	C-7	C-8	C-9	C-10	C-11	C-12	C-13	C-14	C-15
C-1	0	3	2	3	2	3	2	4	3	1	2	3	4	3	3
C-2	2	0	3	3	4	2	3	4	4	2	1	2	3	4	3
C-3	2	1	0	3	2	3	2	2	1	2	1	1	3	2	3
C-4	2	1	2	0	3	1	3	2	3	2	2	1	2	1	3
C-5	2	1	1	2	0	4	2	1	2	3	2	3	3	2	4
C-6	0	3	2	3	2	0	2	4	3	1	2	3	4	3	3
C-7	1	2	3	2	3	3	0	3	1	2	1	2	3	2	3
C-8	2	2	2	3	1	2	1	0	2	1	2	1	3	2	3
C-9	3	2	3	2	2	1	2	3	0	3	2	1	3	2	1
C-10	1	3	2	1	3	2	3	4	3	0	3	2	2	2	3
C-11	2	2	3	4	3	4	3	2	3	2	0	1	2	1	4
C-12	1	2	1	3	3	3	2	3	2	3	2	0	3	2	2
C-13	2	3	1	2	3	2	2	2	2	2	1	2	0	2	2
C-14	1	3	2	3	2	2	1	1	2	3	3	2	1	0	3
C-15	2	4	2	1	3	3	2	2	3	2	1	2	2	3	0

Influence matrix X_7

	C-1	C-2	C-3	C-4	C-5	C-6	C-7	C-8	C-9	C-10	C-11	C-12	C-13	C-14	C-15
C-1	0	2	1	2	1	2	2	2	1	2	2	2	2	1	2
C-2	3	0	2	0	1	3	3	3	2	2	2	2	3	2	1
C-3	3	3	0	1	2	2	2	2	1	1	2	2	2	2	1
C-4	2	4	2	0	2	1	2	2	2	3	1	1	2	2	3
C-5	2	3	2	2	0	2	2	2	2	3	2	2	2	2	3
C-6	4	3	2	2	3	0	3	2	1	2	3	2	2	1	2
C-7	2	2	1	2	1	1	0	1	2	2	1	2	2	1	2
C-8	3	3	3	3	2	2	2	0	3	2	2	2	2	2	3
C-9	2	2	2	2	2	1	2	2	0	2	2	2	2	2	2
C-10	3	3	2	2	2	2	3	3	3	0	2	2	0	2	3
C-11	3	3	2	2	2	2	3	2	1	1	0	2	3	2	2
C-12	4	0	1	1	4	3	3	1	1	2	4	0	3	1	1
C-13	2	3	1	2	2	1	3	2	3	0	2	3	0	2	2
C-14	4	0	1	1	4	1	2	2	2	2	2	1	2	0	2
C-15	2	3	2	2	2	2	2	3	1	2	2	1	3	2	0

Appendix A9

Questionnaire

Barriers to implementation of big data analytics for manufacturing industry

This exercise has two main objectives:

1. To identify the berries in implementing BDA for manufacturing industry.
2. The prioritization and evaluation of the barriers in implementing BDA for manufacturing industry.

<u>Section A: Background information</u>

1. Name of the organization:
2. Year of establishment:
3. Sales turnover in rupees (Optional):
4. Number of employees:
5. Number of professionals: ☐ BE ☐ M. TECH ☐ MBA ☐ Other
6. Nature of products manufactured (Please Tick):

   (a) Product for end user (b) Product for other manufacturer(s)
7. Please tick only one sector which suites best to your organization

☐ Agriculture	☐ Transport
☐ Manufacturing	☐ Healthcare
☐ Entertainment and Media	☐ Financial Services
☐ Telecommunications	☐ Retail
☐ Public sector	☐ Electronics
☐ Automotive	☐ Any Other (Please Specify): IT service management company

Section B: Ranking of barriers to implementation of BDA

Please Rank the following barriers (**Five-point scale: 1- Very low, 2- Low, 3- Medium, 4- High, 5- Very high**) to the implementing big data analytics in manufacturing industry.

S No	Barriers	1	2	3	4	5
1.	Lack of employees support for implementing modern technologies					
2.	Lack of skilled BDA consultants					
3.	Lack of training about BDA to employees					
4.	Lack of trust and commitment among employees					
5.	Lack of data quality					
6.	Unavailability of specific BDA tools					
7.	Lack of coordination among stake holder for BDA related activities					
8.	Complexity in data integration					
9.	Lack of data sharing policy among stake holders					
10.	Lack of capability for using BDA in resource optimization					
11.	Lack of policies for data security and privacy					
12.	Lack of data-driven organizational culture					
13.	Lack of infrastructure readiness					
14.	Lack of awareness about BDA applications for sustainable operations					
15.	Lack of flexible organization culture					
16.	High cost of investment in BDA implementation					
17.	Lack of awareness for sustainable performance measures					

Appendix A10

Questionnaire

Company Background		
1. Name of the Official	**Position /Designation**	**Total Experience (Years)**
2. Name of organisation	**Location/State**	
3. What is the major business/product of your organisation (for example Automotive, Manufacturing, Electrical Appliance, Apparel, Plastics, Mining, Financial Services, Light Equipment etc).		
4. Ownership type of organisation		
a) 100 percent local	b) 100 percent foreign	c) Joint Venture
5. What is the size of your organisation? (No. of employees)		
a) Less than 50	b) 50-100	c) 100–499
d) 500–1000	e) More than 1000	
6. What is the Annual Turnover of your organisation?		
a) Up to 5 Cr.	b) More than 5 Cr but does not exceed 50 Cr.	
c) More than 50 Cr but does not exceed 250 Cr.	d) More than 250 Cr.	
7. What is the total investment in plant and machinery or equipment in your organisation?		
a) Up to 1 Cr.	b) 1 Cr to 10 Cr.	c) 10 Cr to50Cr
d) 50 Cr. to 100 Cr	e) More than 100 Cr	

8. Primary market characteristics? (a) Sell product directly to consumers through retailers (b) Sell component to original equipment manufacturer (OEM) for assembly in the product

<u>Section B</u>

Please Rank the different items of following constructs as applicable for your organization in seven-point scale (1-Strongly Disagree (SD)**,** 2-Disagree (D)**,** 3- Less disagree (LD)**,** 4-Neutral (N)**,** 5-Less Agree (LA), 6-Agree (A)**,** 7-Strongly Agree (SA)}

Construct	**Survey Question**	**Rating**						
		1	**2**	**3**	**4**	**5**	**6**	**7**
Technology competence (TC)	Our company has competence to adopt modern technologies such as big data analytics.							
	Our company has capability for adopting big data analytics							
	Our company is well-versed in implementing big data analytics.							
	Our company has good infrastructure for supporting big data analytics.							
Organizational readiness (OR)	Our organization have sufficient resources for investing in big data analytics.							
	Our organization is ready to allocate adequate resources for adopting the big data analytics.							
	Our organization devotes sufficient financial supports for upgrading technical skills of employees to implement big data analytics.							
	Our current organization structure enables us to adopt the big data analytics							

Government regulation (GR)	The governmental policies encourage us for adopting big data analytics.							
	The government provides incentives/support for using modern technologies such as big data analytics in government procurements and contracts.							
	Government policies support the security and privacy concerns as a consequence of big data analytics application.							
Competitive Pressure (CP)	Our choice to invest in big data analytics is strongly influenced by what competitors are doing.							
	Our company feels pressure from market therefore, we are keen to adopt big data analytics.							
	Our competitors have begun to adopt big data analytics aggressively.							
	If our firm does not undertake big data, we may lose competitive edge over competitors.							
Relative Advantage (RA)	Our company believes that big data analytics could enhance our performance.							
	Our company believes that big data analytics will provide timely information for decision making.							
	Our company feels that big data analytics adoption would result in cost savings.							

	Our company believes that big data analytics could improve the customer service							
Firm Performance (FP)	We believe that big data analytics application will increase the profitability.							
	We believe that big data analytics application will increase operational performance.							
	We believe that big data analytics application will improve return on investment.							
Decision Making capability (DMC)	We believe that big data analytics is an asset for decision-making.							
	We feel that our company will be able to use data for effective decision making.							
	We believe that our organization will be able take the decision effectively by adopting big data analytics.							
	We continuously assess our strategies and take corrective action in response to the insights obtained from data.							
Sustainable organizational performance (SOP)	We believe that big data analytics will protect the environment by improving resource efficiency.							
	We believe that big data analytics will improve sustainable performance of organization.							

	We believe that big data analytics will help to minimize the consumption of resources.							
Supply chain resilience (SCR)	We believe that by adopting big data analytics, our organization will be able to restore material flow after disruption.							
	We believe that by implementing big data analytics, our organization would not take long time to recover normal operating performance after disruption.							
	We believe that by investing in big data analytics, the supply chain would quickly recover to its original state.							
	We believe that by adopting big data analytics, our organization will quickly deal with disruptions.							
Organizational flexibility (OF)	Our organization can rapidly adjust our organizational structure, to adapt to supply chain disruptions.							
	Our organization can respond supply chain disruptions in a cost-effective manner.							
	Our organization is more flexible than our competitors in changing our organizational structure.							
Intention for BDA Implementation (BDAI)	We strongly intend to use BDA in our company.							
	Our company is planning to invest for the adoption of BDA.							
	Overall, we have a favorable attitude of employees towards BDA implementation.							

PUBLICATIONS AND AWARDS

1. Kumar, N., Kumar, G., and Singh, R.K. (2022), "Analysis of barriers intensity for investment in big data analytics for sustainable manufacturing operations in post-COVID-19 pandemic era", Journal of Enterprise Information Management, Vol. 35 No. 1, pp. 179-213. (SSCI and A Category Journal, IF-5.396) https://doi.org/10.1108/JEIM-03-2021-0154
2. Kumar, N., Kumar, G., & Singh, R. K. (2021). Big data analytics application for sustainable manufacturing operations: analysis of strategic factors. *Clean Technologies and Environmental Policy*, *23*(3), 965-989. (SCI, IF-3.636) https://doi.org/10.1007/s10098-020-02008-5
3. Kumar, N., Kumar, G., & Singh, R. K. (2022). Big data analytics forimproving performance of supply chains: A bibliometricanalysis. Twenty First Global Conference onFlexible Systems Management, IIM Shillong.
4. Kumar, N., Kumar, G., & Singh, R. K. (2022). Prioritization of functional areas in manufacturing sector for BDA application. International Conference on Emerging Trends in Mechanical and Industrial Engineering ICETMIE 2022

AWARDS

1. I have received Delhi technological University Commendable Research Award (1st January 2021 to 31st December 2021) which has a Cash value of Rs.50000/ for published research paper, during 5th Research Excellence Awards Ceremony, Delhi Technological University on 03/03/2022.
2. Second research paper also in the queue for the Delhi technological University commendable research award (1st January 2022 to 31st December 2022).